Essays on university-industry knowledge transfer

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Declaration

I certify that the thesis I have presented for examination for the PhD degree of the London School of Economics and Political Science is solely my own work.

I warrant that this authorization does not, to the best of my belief, infringe the rights of any third party.

London, 26th March 2015

Alessandra Scandura

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All errors and omissions remain my own.

Abstract

This PhD thesis explores the determinants and impact of University-Industry (U-I) knowledge transfer. It focuses on the UK as well as a number of European regions and aims at filling several gaps in the literature.

Firstly, I examine the role of scientific (i.e. university) and market (i.e. customers, competitors, suppliers) knowledge for patent inventors working inside firms. I use data from an original survey of industry inventors combined with patent data from the European Patent Office and I employ an econometric strategy rarely applied at inventor's level (i.e. productivity approach). My finding is that the amount and quality of patents invented increase when inventors draw their knowledge jointly from a wide set of knowledge sources, rather than from only one of these.

Secondly, I investigate the impact of U-I research collaborations on UK firms' R&D activities. The data consists of a set of publicly funded U-I partnerships combined with firm-level data available from the UK Office for National Statistics. I combine propensity score matching with OLS regression to select an ad-hoc control group and obtain a reliable estimate of the impact of U-I collaboration on firms. My finding is that treated firms' R&D expenditure and share of R&D employment both increase after participation to U-I partnerships.

Thirdly, I explore the role of research quality as a determinant of UK university departments' engagement in U-I collaboration. I use data on publicly funded U-I collaboration combined with data on UK universities and I employ OLS regression. My finding is that academic quality displays a mixture of negative and positive relationship with the volume of private funding for U-I collaboration, and that this is interdependent with the level of academia's past experience in U-I collaboration.

Together, these chapters make important contributions to a vast but still puzzled literature on U-I knowledge transfer activities.

Introduction

I Overview

This thesis explores the determinants and impact of University-Industry (U-I) knowledge transfer, focusing on the UK as well as a number of European regions. U-I knowledge transfer is a widespread and well-documented economic phenomenon, vastly promoted and fostered by public policy, but also occurring on a voluntary basis. However, the existing empirical evidence is still partial and inconclusive with regards to a number of aspects, hence calling for further research. The thesis aims to fill some of these gaps; it includes the present introductory chapter and three empirical papers, which form the following three chapters of the thesis.

The aim of the introductory chapter is to provide an overarching conceptual framework for the thesis, illustrate the aim of the thesis and present a synthesis of each of the three chapters. I begin with a discussion of some basic concepts providing the background and motivation for my research. Next, I define U-I knowledge transfer activities more in detail, along with their historical trends and geographical dimension. I then illustrate the aim, structure and approach of the thesis, before providing brief summaries of each chapter's objective, results and original contribution, and some final concluding remarks.

II Conceptual framework

II.1 Innovation and knowledge

The importance of University-Industry (U-I) knowledge interactions can be traced back to the characteristics of innovation and knowledge, and how these evolved over time. In fact, the level of understanding of the innovation process and of the process of knowledge generation have changed dramatically during the second half of the twentieth century.

In order to understand innovation, an important distinction is usually made between invention and innovation, as argued by Jan Fagerberg in the introductory chapter of The Oxford Handbook of Innovation (Fagerberg et al., 2006, pag. 4). Invention is the occurrence for the first time of an idea for a new product or process, whereas innovation is the first attempt to put that into practice. However, it is often difficult to make a clear distinction between the two, since they are closely linked to each other. Undoubtedly, both represent continuous processes. Speaking of the innovation process in their influential paper from 1986, Stephen Kline and Nathan Rosenberg characterised it by clearly pointing out what it is not (Kline and Rosenberg, 1986): they used the so-called 'linear model of innovation', according to which the innovation process follows a mechanistic sequence from research to the market, to describe a widespread, but according to them erroneous interpretation of innovation (Fagerberg et al., 2006).[1] The overcoming of the linear model of innovation envisaged by Kline and Rosenberg (1986) was an important landmark in the evolution of the concept of innovation.

The linear model has been found to be inadequate for two main reasons: firstly, it implies a chain of causation from science (research), to development, and finally production and marketing, that only holds for a minority of innovations; secondly, it ignores the many feedbacks and loops that normally occur between the different stages of the process (Kline and Rosenberg, 1986). Instead, innovation has been increasingly regarded as a non-linear and interactive process between firms and their environment (Kline and Rosenberg, 1986; Dosi et al., 1988; Malecki, 1997; Nelson and Winter, 2002). Firstly, non-linearity implies that innovation is not only influenced and determined by engineers and scientists working in R&D or by the top management, but also by actors and sources of information both inside and outside the firm. Secondly, the innovation process is defined interactive since a wide set of collaborations may affect the innovation capacity of firms. These are both intra-firm interactions between departments

[1] The exact source of the linear model is unknown, having never been fully documented. However, as reported by Godin (2006), a number of authors argue that it comes directly from Vannevar Bush *The Endless Frontier* (Bush, 1945). See e.g. Freeman (1996); Hounshell (1996); Mowery (1997); Stokes (1997).

and extra firm collaborations with other firms, knowledge providers such as universities and research centres, public agencies and others.

Similarly, the debate on the economics of knowledge has evolved through different stages, depending on the characteristics assigned to knowledge across time. On the basis of the seminal works of Arrow (1962) and Nelson (1959), knowledge was firstly considered a public good. Accordingly, its properties include the fact that it may spill over (mainly from universities) and it is freely available (mainly to firms). Afterwards, a quasi-proprietary feature has been attached to knowledge (Nelson and Winter, 1982), emphasizing its stickiness, or, in other words, the inability or difficulties to transfer it (Foray, 2004). In this view, the firm is considered the privileged place where knowledge is created and accumulated. Finally, several more recent contributions have brought a shift towards the concept of knowledge as a collective process (see e.g. Kauffman, 1993; Weitzman, 1998), centered on (the role of) external knowledge generated by interactions among various economic agents (see a.g. David, 1992; Griliches, 1992; Cooke et al., 2002).[2]

At the core of the collective knowledge approach is that knowledge generation and utilisation can be viewed as the outcome of a recombination process, according to which innovations stem either from the combination of brand new components or from the combination of existing components in new ways (see e.g. Kauffman, 1993; Weitzman, 1998).[3] In particular, in this view, firms are regarded as dynamic and creative agents in search for knowledge in the local environment. Interactions among firms, universities and research centres are hence considered fundamental for the generation, diffusion and absorption of new knowledge. Knowledge can be transferred and disseminated among agents in the economic system and the spillovers hence generated bear positive externalities to firms by stimulating innovation activities and productivity. According to this approach, universities

[2]The idea that innovation and particularly, inventions are produced collectively has also been put forward by Allen (1983): on the basis of the historical examination of the British blast furnaces industry in the nineteenth century, he proposes that inventions take place in a collection of firms whose interactions would collectively invent.

[3]In his seminal works, Schumpeter (1912, 1942) proposed to view innovation as the outcome of a recombination process, arguing that most innovations stem from the recombinations of existing elements in new ways; however, the contributions by Weitzman (1998, 1996) represent the former attempt to draw upon such assumptions (Krafft and Quatraro, 2011).

that are able to participate into the flows of knowledge interactions are crucial sources of external knowledge to firms (Cassia et al., 2009).

II.2 Systemic approaches to innovation

The non-linear and interactive characteristics of the innovation process, together with its systemic nature, have been fully acknowledged in a number of theoretical and conceptual frameworks that explain how innovation is created. The well known 'innovation systems' or 'systems of innovation' (SI) approach, introduced by evolutionary economists of technological change in the late 1980s (see e.g. Freeman, 1987; Lundvall, 1988, 1992), is based on the argument that what appears as innovation at the macro level is the result of an interactive process that involves several actors at the micro level. Initially, although this approach had nothing inherently spatial, the set of firms, organisations and institutions involved in such process formed in many cases a sort of 'national' community, so to talk about national systems of innovation (NSI) (Lundvall, 1992; Nelson, 1993; Nelson and Rosenberg, 1993; Edquist, 1997). The prolific literature on NSI argues that the performance of national economies cannot be explained only in terms of the strategies and performance of firms, but other factors and actors play crucial roles in favouring the generation and diffusion of knowledge, including: inter-organisation networks, financial and legal institutions (e.g. intellectual property rights), technical agencies and research infrastructures, education and training systems, governance structures, innovation policies (Iammarino, 2005).

The NSI approach has later branched out into two directions. Firstly, it has been recognised that the borders defining the set of relevant actors and interactions may have a smaller scale than the national one, notably a regional dimension, and thus it is possible to identify different regional systems of innovation (RSI) (Autio, 1998; Braczyk et al., 1998; Cooke, 2001; Asheim and Isaksen, 2002; Asheim et al., 2011). An RSI can be defined as the 'localised network of actors and institutions in the public and private sectors whose activities and interactions generate, import, modify and diffuse new technologies, within and outside the region' (Archibugi et al., 1999; Evangelista et al., 2002). Similarly, several other units of analysis have become popular, including 'milieux innovateurs' (Aydalot, 1986), 'new industrial districts' (Becattini, 1987), 'technological districts' (Markusen, 1985; Storper, 1992; Markusen, 1996), 'learning regions' (Asheim, 1996; Morgan, 2007). Focusing on the sub-national model allows to appreciate the importance of contextual elements and the presence of systemic interactions in the process of generation and diffusion of innovation as key determinants of regional or, more generally, local technological and economic performance (Iammarino, 2005).

Secondly, it has also been suggested that both the actors in the system and how these are connected to each other may significantly vary across sectors so that innovation systems also have a sectoral dimension (Breschi and Malerba, 1997; Malerba, 2002, 2004). Accordingly, a sectoral SI is made up of a set of new and established products for specific uses along with the set of actors that carry out market and non-market interactions for the creation, production and sale of those products (Malerba, 2002). Organisations involved include firms, as well as non-firm organisations (e.g. universities, government agencies, financial and technical institutions).

The idea of knowledge and innovation as interactive phenomena is also at the core of the so called Triple Helix model (TH) (Leydesdorff and Etzkowitz, 1996, 1998; Etzkowitz and Leydesdorff, 1997, 2000), based on the argument that the university plays an enhanced role in innovation, especially in increasingly knowledge-based economies. According to the TH model, the 'entrepreneurial university' is at the centre of a triadic relationship with industry and government in that it takes a pro-active stance in putting knowledge to use and in creating new knowledge. In its more complete formulation, the TH approach considers an overlapping knowledge infrastructure where each of the three actors takes the role of the other (Etzkowitz and Leydesdorff, 2000). Similarly to the SI approach, in the original formulation of the TH model there was no or little attention to spatial dimensions other than the national one. However, at a later stage, such national bias has been overcome introducing more fine-grained geography (Iammarino, 2005). Hence, the primary role of universities became very much related to the localities in which they are embedded.

II.3 The role of university

The concept of the 'entrepreneurial' university has been put forward by Etzkowitz (1983). In his study of American entrepreneurial universities in the 1980s, Etzkowitz (1983) noted that in that period of increasing costs and static government funds, universities were beginning to consider the possibility to source additional funding from patenting the discoveries made by academic scientists, from the sale of results of research carrried out under contracts with companies, and from engaging into partnership with businesses. In other words, universities were taking on an 'entrepreneurial' attitude. The importance of academic research to industry and to society as a whole has gained novel appreciation since then. Similar trends were taking place in Europe as well, as illustrated by Clark (1998) in his study of five European universities: in fact, among the ingredients of success in each institution he noted an integrated entrepreneurial culture.

In addition, universities across the world, and mainly in developed countries, have received increasing calls to incorporate regional economic development in their traditional mission (Fayolle and Redford, 2014). As a response, many universities embraced a new entrepreneurial role under which they not only intensified their efforts to generate revenues from research there conducted, but they also become engines of local economic growth (Charles, 2003; Goldstein, 2009).

The idea that universities can contribute to the development of a territory, including its innovative performance, rests upon two key assumptions: in the first place, universities increase the production of knowledge by supplying new skilled workforce (university first mission) and the results of scientific research (university second mission); secondly, the presence of universities in a territory can lead to U-I knowledge transfer and exchange (university third mission) (Veugelers and Del Rey, 2014). Therefore, the ways for universities to contribute to local development are the provision of excellence in education, in research and in knowledge transfer. Furthermore, the paradigm of the entrepreneurial university (Etzkowitz et al., 2000) and the shift towards the knowledge based model of economic development, legitimate universities to pursue their own profits, aside acting as a central agent in the process of knowledge production and generation (Lawton Smith and Bagchi-Sen, 2006).

Turning to a more evidence-based perspective and in line with the idea of the entrepreneurial university at the core of the TH model, there are four not mutually exclusive reasons for why universities have such a key territorial role, particularly in U-I linkages (Lawton Smith, 2007). Firstly, there is evidence that agents involved in innovation activities are geographically concentrated in the early stages of some industries' life cycle (such as biotechnology) (Breschi and Malerba, 1997; Audretsch, 1998) and, on the contrary, they tend to be more dispersed at later stages of the life cycle: firms can access and absorb knowledge more easily when located close to each other and close to the scientific community through interaction and face-to-face communication. Secondly, firms locate around universities in order to take advantage of localised knowledge spillovers. These, defined as flows of ideas between agents at less than the original cost (Griliches, 1992), are externalities that are bounded in space and thus represent an incentive for firms' co-location. Thirdly, there are cost advantages to a firm being near to a university. This is because the concentration of innovative firms results in agglomeration economies (Scott, 1988). Fourth, in line with the previous assumptions (Veugelers and Del Rey, 2014), the major contribution of universities to territorial development is through the supply of knowledge in the form of skilled people, which in turn can absorb knowledge (Dankbaar, 2004).

Against this background, it is clear that interactions between actors in a system are fundamental for the realisation of successful innovation processes. Moreover, whether we take the stance of the innovation system or triple helix or any other similar approach, it appears that industry and universities are at the core of the innovation process. Therefore, U-I knowledge interaction becomes a fundamental driver of innovative performance of knowledge-based economies (OECD, 1998, 2002a), particularly of localities.

III U-I knowledge transfer activities in context

III.1 Definition and historical trends

Nowadays U-I knowledge transfer is commonly understood as a broad concept identifying a wide set of interactions between firms and universities that are aimed at the exchange of knowledge related to research, science and technology (OECD, 1998, 2002a; Agrawal, 2001). These include employment channels, such as temporary personnel exchanges between university and industry or recruitment of graduates; intellectual property rights related interactions, such as patent ownership agreement and licensing; research collaboration, indicating U-I collaborative R&D research projects (research partnerships, consultancy project and research consortia); and informal direct/indirect contacts such as publications, conferences and informal meetings (see e.g. Geuna and Rossi, 2013; Rossi and Rosli, 2013).

U-I linkages emerged as a distinctive and growing phenomenon in most advanced countries from the 1980s onwards (Geuna and Muscio, 2009). Before that, particularly in the aftermath of the Second World War, industry in developed economies relied on universities mainly for the provision of highly skilled personnel for own R&D laboratories. The latter represented the main responsibility for universities together with that of publishing scientific results of their research activity (OECD, 1998). To some extent, academic scientists had developed networks of interactions with firms and government, but mainly acting on personal basis without any involvement of the university, and industry had supported university research, usually through endowments and gifts rather than specific projects and contracts. For instance, in both the United States and Europe, large companies with R&D laboratories dedicated to basic research played a special role, and academic researchers often collaborated with company scientists (Geuna and Muscio, 2009).

However, U-I interactions in their more general definition of public-private partnerships were not an entirely new phenomenon. In fact, collaboration between public research and industry has characterised the German research system since the nineteenth century. In the United Kingdom, collaboration between university departments in science and engineering and industry was not uncommon at the beginning of the twentieth century and often involved academics working as consultants to industry, although this type of interaction was later replaced with the development of industrial laboratories (OECD, 1998). In post-war Japan, public-private partnerships have been an integral part of large industrial technology programmes sponsored by the government with the aim to help Japan catch up in specific sectors. In the United States, university engagement with business can be traced back to the second half of the nineteenth century, when land grant universities pursuing 'more practical research strategies' have been created, aside the foundation of liberal arts universities oriented toward pure research (Etzkowitz and Leydesdorff, 2000). However, it was not until the Cold War that changes in government policy, led by heightened defence spending on R&D, resulted in increased collaboration between public research and industry. By the early 1980s, the success of Japanese collaborative R&D and growing competition in global technology markets led to a paradigm shift in the United States, with public-private partnerships becoming a key tool of federal technology policy for improving national competitiveness (OECD, 1998).

Increasing globalisation and competition, together with a stronger emphasis on innovation from the 1980s onwards, brought about many changes in the relationship between university and industry. Firstly, views changed regarding the role of universities in the economy: from being seen as 'ivory towers' where academics mainly performed research in isolation, universities became an economic organisation actively engaged with external stakeholders (Freitas et al., 2011). In particular, universities in developed countries became more interested in collaborating with companies because of the decrease of government research funding for military purposes and, more generally, reduction of government intervention in the economy (Geuna and Muscio, 2009).[4] Moreover, many governments began to introduce incentives for university to engage in activities with industry, on the basis of the assumption that U-I interaction increases the rate of innovation in the overall economy (Spencer, 2001).

Secondly, due to competition pressures and increasing speed and complexity of knowledge processes, as well as declining profits and increasing costs of research, companies needed to get closer to external sources of knowledge in order to innovate. As a consequence, industry became increasingly interested in university research as well as highly skilled personnel to create and exploit new knowledge (Freitas et al., 2011). As it was the case for university, many governments in advanced economies implemented innovation policies with the aim to support companies' interaction with universities. As a matter of fact, the scale and scope of university-

[4]For the United States, especially, the fall of the Berlin Wall meant a significant reduction in military spending in universities, although this trend was already underway (Geuna and Muscio, 2009).

industry knowledge transfer activities have increased over time (see e.g. OECD, 1998, 2002a; Geuna and Muscio, 2009; Rossi, 2010; Freitas et al., 2011; OECD, 2013), as shown by the growing number of university-assigned patents, academic papers co-authored with industry, income from royalties, and industry funding for academic research.

III.2 Motivations for U-I knowledge transfer

From a theoretical standpoint, firms engage into U-I activities to overcome market failures that result from uncertainty of the R&D process, resource constraints and the inability to internalise significant spillovers (see e.g. Dasgupta and David, 1994; Martin and Scott, 2000; Salter and Martin, 2001). Therefore, U-I interaction is a *market* response to market failures that prevent firms from conducting the socially optimal level of R&D. Similarly, public support of U-I initiatives is a *policy* response to market failures that are not overcome by the market alone.

Empirically, it has been shown that firms' motivation for U-I knowledge transfer include accessing research infrastructure, accessing expertise, finding support for renewal of firm's technology, gaining access to potential employees, expanding contacts for corporate laboratories, increasing pre-competitive research, leveraging internal research capabilities, reducing and sharing research costs (see e.g. Hagedoorn, 1993; Steurs, 1995; Cassiman and Veugelers, 2002; Lopéz, 2008; Bruneel et al., 2009).

Universities, on the other hand, are pushed towards engagement in U-I activities as a consequence of budgetary constraints faced by governments and their impact on patterns of funding of university research, as well as the higher costs of research in general (Geuna and Muscio, 2009). Therefore, universities' motivation for U-I knowledge transfer include obtaining financial support for their mission, broadening the study and research experience of students and faculty, identifying interesting and significant research problems, increasing employment opportunities, enhancing local economic development (Larsen, 2011; Geuna and Rossi, 2013; Perkmann et al., 2013).

IV Recent literature on U-I interaction and existing gaps

IV.1 Empirical evidence

U-I linkages emerged as a specific and consolidated field of study around three decades ago. This was spurred on the one hand, by the rapid growth of published research adopting a 'system of innovation' perspective, or other types of network views, towards the organisation of higher education, research and industrial innovation and, on the other hand, by an increased policy emphasis on the commercialisation of research and the creation of a closer relationship between basic research and society (Gulbrandsen et al., 2011). In fact, from the mid 1980s onwards many countries encouraged greater interaction between universities and firms by changing the legislation and creating ad-hoc support mechanisms.

Research on U-I knowledge transfer has been categorised into at least four groups (Agrawal, 2001), depending on the focus of the research, being this on firms, universities, the geography of interaction or the channels of knowledge transfer. In addition, within each category it is also possible to distinguish studies that mainly look at the determinants of U-I knowledge transfer, and those that look at its impact.

Firstly, there are studies on firms' characteristics, that focus on issues related to the firm side of U-I interaction, especially the characteristics that influence firms' ability to utilise externally generated knowledge, such as internal organisation, resource allocation and partnerships (see e.g. Cohen and Levinthal, 1990; Cockburn and Henderson, 1998; Ziedonis, 1999; Audretsch, 2000; Zucker et al., 2000), but also the impact of U-I interaction on firms' R&D and innovation activities (see e.g. Becker, 2003; Fritsch and Franke, 2004; Arvanitis et al., 2008; Lööf and Broström, 2008).

Secondly, there are studies that investigate the university side, thus focusing on issues that include the characteristics that influence universities' ability to interact with firms, university policies regarding intellectual property rights, licensing strategies employed by university technology licensing offices, and characteristics of the actual inventor-professors, as well as the impact of U-I interaction on academic research (see e.g. Henderson et al., 1998; Feldman et al., 2002; Thursby and Thursby, 2002; Di Gregorio and Shane, 2003; Larsen, 2011).

A third stream of literature has developed around the geography of U-I interaction in terms of localized knowledge spillovers, considering the spatial relationship between firms and universities relative to performance in terms of knowledge transfer success (see e.g. Jaffe, 1989; Jaffe et al., 1993; Audretsch and Feldman, 1996; Zucker et al., 1998). Papers in this literature[5] often point to the role of geographical proximity for U-I interaction and to the factors that influence location decisions both from private and public perspectives (Agrawal, 2001).

Lastly, there are studies on the channels of knowledge transfer, that examine the relative importance of various transfer channels between universities and businesses, such as publications, patents, consulting, recruiting, joint ventures, research contracts, and informal meetings (see e.g. Cohen et al., 1998, 2002; Agrawal and Henderson, 2002; Colyvas et al., 2002; Shane, 2002; D'Este and Patel, 2007; D'Este and Perkmann, 2011).

IV.2 U-I interaction and geography

The literature on university-industry knowledge transfer has devoted a great deal of attention to the geography of interactions, particularly to the role of geographical proximity. The argument commonly held is that spatial proximity to universities provides an advantage for firms that are willing to keep abreast of scientific developments, as it facilitates personal interactions and exchange, and face-to-face contacts (see e.g. Jaffe, 1989; Feldman, 1994; Henderson et al., 1998; Mansfield, 1995; Anselin et al., 1997; Cooke, 2001; Arundel and Geuna, 2004; Abramovsky et al., 2007; Fritsch and Slavtchev, 2007; D'Este and Iammarino, 2010; D'Este et al., 2013). Accordingly, firms located nearby universities are more likely to interact with universities and thus to benefit from knowledge spillovers.

The underlying assumption is one about knowledge and geography:

[5]More recent contributions include e.g. Arundel and Geuna (2004); Abramovsky et al. (2007); Fritsch and Slavtchev (2007); D'Este and Iammarino (2010); Laursen et al. (2011); D'Este et al. (2013). See section IV.2.

companies located nearby universities are more likely to benefit from knowledge externalities from academic research, as spatial proximity facilitates the interactions and face-to-face contacts necessary for the transmission of the tacit component of knowledge. In fact, while the codified component of knowledge is transferred among firms and universities through knowledge codified in journal publications and seminars, the tacit component spills over in oral conversation and face-to-face contacts, hence facilitated by spatial proximity (Cassia et al., 2009).[6] In other words, knowledge that spills over from academia can be defined as a public but also local good (Breschi and Lissoni, 2001).

In addition, two other mechanisms have been proposed as conducive to academic knowledge spillovers. Firstly, knowledge flows from academia to the economic system and generates new market opportunities for firms. In accordance with the Knowledge Spillover Theory of Entrepreneurship proposed by Audretsch (1995), this mechanism entails the creation of a new firm from the knowledge producing entity. New entrepreneurial opportunities are generated from new knowledge left uncommercialised, which spills over from academia, research centres and other firms (Cassia et al., 2009). Secondly, mobility of human capital is another mechanisms through which knowledge can be transferred. In fact, it has been shown that the availability of skilled labour force from universities has a positive effect on knowledge transfer (see e.g. Powers, 2003; O'Shea et al., 2005; Audretsch and Lehmann, 2005).

Although geographical proximity is frequently claimed to be beneficial for successful collaboration and knowledge exchange, in many cases such localised interaction is only implicitly assumed rather than explicitly scrutinised. For this reason, several works have theoretically questioned the importance of geographical proximity *per se* for collaboration and knowledge exchange (see e.g. Breschi and Lissoni, 2001; Howells, 2002; Gertler, 2003; Torre and Rallet, 2005; Boschma, 2005). The main argument is

[6] The concept of tacit knowledge was first introduced by Polanyi (1966), who explains that tacit knowledge cannot be expressed outside the action of the person who has it. Its distinctive characteristic is its incorporation in thoughts, and its invisibility, even for those who possess it and use it 'automatically' (Foray, 2004): it follows that tacit knowledge is difficult to transfer. Instead, codified knowledge, or explicit knowledge, is highly codified, as in blueprints, manuals, recipes, or in the form of training: therefore, it is relatively easy to transfer (Fagerberg et al., 2006).

that ‘simple’ co-location is ‘neither a prerequisite nor a sufficient condition’ for collaboration (Boschma, 2005, pag. 71). Other forms of proximity (e.g. cognitive or technological, organisational, institutional, social) may well be at least as important as geographical proximity for interaction and knowledge exchange. Also, geographical proximity may compensate for the lack of other forms of proximity (and vice versa). For instance, co-location can positively influence the building of mutual trust due to frequent face-to-face contacts, hence helping to overcome organisational differences (e.g. university versus firms) (Boschma, 2005), as much as institutional proximity can facilitate interactions over long geographical distances (Ponds et al., 2007) and technological proximity can play a moderating role on physical distance (Quatraro and Usai, 2014).[7] In sum, studies of various forms of proximity tend to point to a relatively indirect role for the spatial dimension in fostering knowledge creation and diffusion (D’Este et al., 2013): accordingly, geographical proximity may rather act as a bridging and reinforcing factor for other forms of proximity (see e.g Kirat and Lung, 1999; Nooteboom, 1999; Torre and Gilly, 2000; Boschma, 2005; Torre and Rallet, 2005; Ponds et al., 2007; Vicente et al., 2007; Balconi et al., 2011; D’Este et al., 2013).

In addition, it is worth noting that research on the geographical dimension of university-industry collaborations shows that these linkages are not limited to the local/regional level, as they often occur on the national or even the international scale (see e.g. McKelvey et al., 2003; Ponds et al., 2007; Hoekman et al., 2009). These findings are in line with the increasing attention to the non-regional dimension of knowledge flows (Bunnell and Coe, 2001; Faulconbridge, 2006; Ponds et al., 2010). It follows that knowledge spillovers are expected to occur over long distances. If and when this may be the case, it is unlikely that the relationship between academic knowledge spillovers and regional innovation is fully captured by taking only the regional dimension of spillovers into account (Ponds et al., 2010).

[7] Organisational proximity is defined by Boschma (2005) as the extent to which relations are shared in an organisational arrangement, either between or within organisations. Institutional proximity can be defined as the set of common habits, routines, established practices, rules, or laws that regulate the relations and interactions between individuals and groups (Edquist, 1997). Technological or cognitive proximity refers to the cognitive base of actors and organisations and, thus, their absorptive capacity and potential for learning (Boschma, 2005).

One reason for the great attention devoted by scholars to the role of geography for U-I interaction and, more generally, to localised knowledge spillovers from academic research, is due to the direct policy implications that works in this area of inquiry are likely to have. In fact, extant research points at factors that influence firms location choices (e.g. location of universities), as well as factors that the government should consider when allocating university research funding. Given the intrinsically tacit component of knowledge spillovers, policy decisions regarding the allocation of research funding across space may have significant impacts on local economies (Belenzon and Schankerman, 2013). Nonetheless, recent work point out that the analysis of the geographical factor itself may not be enough to fully understand knowledge spillovers, as they also occur over long distances. Indeed, as envisaged by Agrawal in his overview of unanswered questions on U-I knowledge transfer from 2001 (Agrawal, 2001), current effort is being directed towards border effects on spatial relationships and knowledge spillovers (see e.g. Ponds et al., 2010; Belenzon and Schankerman, 2013; Quatraro and Usai, 2014).

IV.3 Some gaps in the literature

Within the innovation literature there are plenty of contributions looking at U-I interaction from the standpoint of firms, universities and localities. Instead, there is only scant evidence on individual knowledge users/producers inside companies, such as patent inventors. However, innovation is not just the product of firms and other organisations (e.g. universities, public and private research centres) because it ultimately requires individual creativity (Huber, 1998). As a matter of fact, empirical evidence about university inventors is vast, partly because of a large amount of information publicly available, whereas evidence on industrial inventors is rather limited and not conclusive yet. The focus of research has only recently moved down to the level of individual inventor inside the firm (see e.g. Giuri et al., 2007; Hoisl, 2007; Mariani and Romanelli, 2007; Weck and Blomqvist, 2008; Schneider, 2009; Pasquini et al., 2012), thus scholars have, so far, only partly answered questions concerned with the role of U-I knowledge transfer for private inventors. This is a relevant issue in light of the fact that private R&D activities still remain, to some extent, a black box and the individual perspective might shed some new lights on that. With the aim to fill this gap and add to a small but growing literature, in the first chapter of my thesis I consider patent inventors employed by companies located in three European regions and investigate the role of a wide set of knowledge sources for their inventive activity.

Secondly, although the study of the impact of scientific knowledge and U-I knowledge transfer on firms' performance has attracted much attention from different strands of the academic literature (see e.g. Criscuolo and Haskel, 2003; Belderbos et al., 2004; Faems et al., 2005; Cassiman and Veugelers, 2006; Frenz and Ietto-Gillies, 2009), evidence is still mixed. To some extent, there seems to be convergence towards the conclusion that U-I interaction positively affects firms' R&D and productivity, but this is far from being unquestionable. In addition, the motivations for evaluating the impact on firms' overall economic performance or innovative activities (or both), remain often unclear. In other words, it is still an open issue whether U-I interaction's effects should be searched on firms' R&D input (e.g. R&D expenditure) or output (e.g. patents) or overall performance (e.g. labour productivity). This calls for further research that has considerable academic as well as policy interest. I attempt to shed new light on the effect of U-I knowledge transfer activities on firms in the second chapter of my thesis, in which I carry out a policy evaluation study to investigate the impact of publicly funded U-I collaborative partnerships on UK firms' R&D activities.

Thirdly, as far as universities are concerned, the role of individual-level factors is well explored within the literature on the determinants of U-I interaction, whereas evidence is scant when it comes to the organisational context in which academic engagement occurs. This is especially the case with respect to the characteristics of university departments involved in U-I interaction (Perkmann et al., 2013). Moreover, there is an extensive empirical evidence on the determinants of U-I collaboration (see e.g. Schartinger et al., 2002; D'Este and Patel, 2007; D'Este and Iammarino, 2010; D'Este and Perkmann, 2011; D'Este et al., 2013), but only rarely is the volume of financial resources (both private and public) at stake accounted for. Instead, the income that universities receive from public agencies as well as companies for their knowledge transfer activities may mirror the value that external partners place on the knowledge they receive from universities (Rossi and Rosli, 2013). Therefore, in my third chapter I attempt to overcome these limitations by considering the flows of private, as well as public, financial resources involved in U-I partnerships with the aim to bring new evidence on the role of organisation level determinants for U-I knowledge transfer. In particular, I take the case of publicly funded U-I collaboration in the UK to study the relationship between academic quality and the flows of financial resources involved.

V Thesis objectives and approach

V.1 Aim of the thesis

This thesis investigates a number of aspects of U-I knowledge transfer from the standpoint of both firms and universities, which are related to its economic impact and determinants. The aim is to fill some important gaps in the literature, underlined in the previous section and that will be thoroughly illustrated in the following of the thesis. This thesis contributes to the innovation literature on science-business links and, particularly, on different strands of studies that touch upon this topic, including economics of innovation, management of innovation, and science and innovation policy studies.

In the first place, this thesis addresses the innovative activity of patent inventors employed by companies in three European regions (West and East Midlands, United Kingdom; Piedmont, Italy; Catalonia, Spain), with the objective to shed new light on the drivers of innovation at individual level and the role of university knowledge as compared to other sources of knowledge. In particular, the research question that the first chapter answers is *'Do industrial inventors that use various sources of knowledge in their inventive activity display higher performances that those who do not?'*. The hypothesis tested is that inventors' performance does benefit from the joint use of a wide set of knowledge sources, including knowledge from universities, public research centres, competing firms, suppliers and consultancy. The findings of this chapter contribute to the literature on the management of technology and innovation, particularly of inventive processes.

The second chapter of the thesis examines the effect of U-I knowledge transfer on firms' R&D activities, with the aim to shed new light on the impact of science and innovation policy on private R&D. The research question addressed in this chapter is *'What is the impact of publicly funded U-I collaboration on firms' R&D activities in the UK?'* In order to answer this question, a policy evaluation study is carried out and the hypotheses that publicly funded U-I research collaborations have a positive impact on firms' R&D expenditure and R&D employment are empirically tested. This chapter adds to the innovation literature that is concerned with the evaluation of science, technology and innovation policy.

Lastly, I investigate the university determinants of U-I knowledge transfer, with the goal of uncovering the role of research quality together with other factors for academic engagement with industry in the UK. The driving question of the third chapter of the thesis is *'What is the role of department level characteristics for UK universities' engagement in U-I collaboration?'*. I test the hypotheses that research quality negatively affects U-I engagement and that this relationship is influenced by academia's past experience in U-I collaboration. This chapter contributes to the literature on science policy and management of innovation.

V.2 Structure and approach of the thesis

Each of the three research questions and related hypotheses illustrated above is tested in an empirical paper. Each of them forms a chapter of the thesis and includes introduction, literature review and hypotheses development, presentation of data and methodology, followed by the discussion of the results and concluding remarks.

My approach builds on economics of innovation concepts and frameworks. The research draws on quantitative methods, particularly econometric analysis. I apply a number of econometric techniques on newly created micro-level datasets that result from the combination of brand new data sources as well as existing raw datasets with several other micro data sources. In particular, I use a novel survey of patent inventors combined with patent data from the European Patent Office, an existing dataset of U-I collaboration combined with firm-level data provided by the UK Office for National Statistics, and the above-mentioned dataset of U-I collaboration combined with university information gathered from the UK Higher Education Funding Councils.

In spite of the fact that the investigation of U-I knowledge linkages is very often intertwined with spatial issues, the role of geography in this thesis is relatively limited, although this differs across the three empirical papers. The reason for this is twofold. Firstly, the use of geographical data has been constrained by lack of data and data limitations. Secondly, from the reviews of the literature carried out in each chapter, it emerged that issues related to the impact of U-I interaction on firms and its determinants at the level of academia, were among the most relevant unresolved as well as debated ones. These are complex issues per se, hence needing a great attention in order to grasp their profound link with U-I interaction. Adding layers of complexity by including the spatial dimension, or by considering other aspects such as the role of various channels of knowledge transmission may have led to less precise answers to the research questions addressed. Therefore, in order to properly investigate the determinants and impacts of U-I knowledge transfer activities, a limited role has been given to other relevant factors, including that of geography. Future research stemming from this thesis will certainly take those into account.[8]

Nonetheless, the spatial dimension, particularly the regional one, is relevant in the first chapter, as this addresses regional inventive activities and it relies on a survey administered at regional level. In particular, the study highlights different regional patterns as far as the production of patents in concerned, whereas no significant differences emerge as far as patent quality is concerned. In the second chapter, the focus is on U-I interaction in the United Kingdom, particularly those funded by a specific national-level policy program, hence the geographical standpoint is limited to the national scale. Nonetheless, a great deal of attention is dedicated to the formulation of the empirical strategy, in which the spatial unit of analysis employed to perform the chosen methodology has a key role for the outcome of the analysis. The third chapter, similarly to the second one, investigates national U-I collaborations, with a special attention to the relationship with academic quality. Although the role of geography is limited to the employment of region-level dummies in the empirical analysis, the findings of this paper are highly related to policy issues such as the allocation of research funds to universities. This, as underlined in

[8]See section VII.

paragraph IV.2, is likely to have significant impacts on local pattern of growth and development.

In the next section I provide short summaries of the three chapters, in which I underline their aims, findings, data and methods employed, and provide details on their contributions to the literature. These chapters also provides some insights for policy, which will be underlined in the concluding section of the present chapter.

VI Summary of the chapters

VI.1 The role of scientific and market knowledge in the inventive process

The first chapter of the thesis investigates U-I knowledge transfer activities in three European regions by looking at industry inventors' patterns of interaction with organisations (both firms and non-firms) that are external to the company where they are employed. The aim of this chapter is to study the relationship between U-I - as well as Industry-Industry - knowledge transfer and patenting activity. In particular, I compare the role of knowledge from university and other research organisations ('scientific knowledge') with that of knowledge from market sources ('market knowledge', e.g. from clients and customers, direct competitors, or suppliers) for the inventive activities carried out by inventors working within firms: I hypothesise that the joint use of scientific knowledge and market knowledge has a higher impact on the inventors' performance than the separate use of each of the two knowledge sources.

The empirical analysis is based on an original survey of industrial inventors[9] that provides new insights about the demand of knowledge expressed by the actors directly involved in the innovative process in their regional systems of innovation. By combining the data obtained from the survey with patent-level information from the European Patent Office, I create a novel cross-section dataset of inventors' data that allow to test my hypothesis and control for a number of individual and patent level characteristics.

[9] PICK-ME Survey, Grant agreement n. SSH-CT-2010-266959.

To analyse the role of different knowledge sources for inventors' performance, I employ the so-called productivity approach (Cassiman and Veugelers, 2006), in which inventors' knowledge sourcing strategies are used as explanatory factors for inventors' performance. To the best of my knowledge, this is one of the first attempts to apply this approach at the inventor's level. My finding is that the amount and, to a lesser extent, the quality of patents invented by industry inventors in the selected European regions increase when inventors draw their knowledge jointly from scientific and market sources, rather than from only one of these. Heterogeneity exists across mobile and non-mobile inventors, especially as far as the quality of inventions is concerned; furthermore, the results show that inventors' performance, notably in terms of quantity of patents, differs across different regions.

The findings of this chapter offer several contributions to the literature. While previous evidence has mainly looked at the role of organisational-level factors and patent features in explaining the outcomes of innovative activities (see e.g. Hall et al., 2005; Harhoff et al., 1999; Pasquini et al., 2012; Suzuki, 2011), the focus of this chapter is on the individual who is primarily responsible for the inventive activity. Therefore, inventors' decisions are taken into account as fundamental drivers of individual outcomes. Existing evidence shows that inventors rely on different sources of knowledge to increase the chances of patent commercialisation (Pasquini et al., 2012), although the opposite holds for the value of patented inventions (Schneider, 2009). This study adds that quantity as well as quality of inventors' patents benefit from the recombination of different sources of external knowledge. This is a relevant result because it supports the idea that knowledge exchange across organisations should be adequately backed up, not only at organisation level (i.e. the firm) but also at individual level.

VI.2 University-Industry collaboration and firms' R&D effort

The aim of the second chapter of the thesis is to investigate the impact of U-I knowledge transfer on firms' R&D efforts. To do that, I carry out a policy evaluation study to assess the impact of U-I collaboration on UK firms' R&D intramural expenditure per employee and the share of R&D personnel. In particular, the empirical analysis assesses the impact of a set of university-business research partnerships funded by the Engineering and Physical Science Research Council (EPSRC), which is one of the major research councils in the UK.

After a review of the related literature and analysis of policy documents, I argue that the impact of the EPSRC U-I research projects should be searched on firms' R&D inputs, because of their pre-competitive nature. I focus on both R&D intramural expenditure and the share of R&D employment, since the former may capture differences in equipment and/or costs, whereas the latter may mirror a human capital component of R&D that is usually more permanent (Busom, 2000), and I expect that both of them increase after participation to the projects.

The empirical analysis of this chapter relies on a unique micro-level dataset, resulting from the combination of a dataset of EPSRC U-I partnerships funded between 1998 and 2007 with firm-level data gathered from two databases provided by the UK Office for National Statistics (ONS): the Business Structure Database (BSD), which provides basic information about firms, and the Business Expenditure on R&D database (BERD), providing R&D data collected through an annual survey carried out by the ONS.

In order to assess the impact of U-I research projects on participating firms, I select a control group of untreated firms on the basis of pre-treatment characteristics via propensity score matching and then compare the performance of treated and untreated firms via ordinary least squares regression. For the development of the methodology of this study, especially for the estimation of the probability that firms participate to U-I projects, a number of factors are fundamental. These include firms' characteristics and geographical factors. Notably, the latter allow to match treated firms with non-treated ones that are located in the same area, hence to assume that they are subject to similar external factors and benefit from the presence of the same universities and other organisations.

My finding is that EPSRC U-I collaborations funded between 1998 and 2007 have a positive impact on both outcome variables three years after the beginning of U-I projects and the figures are very similar across several matching methods employed for the selection of the control group. This is an important result as it proves the relevance of public research for business R&D activities and, more generally, the role of university as a driver of innovation through its third mission.

This study provides a number of contributions to the academic literature. Existing evidence is contradictory with respect to whether the impact of research collaboration, and more generally, U-I interaction, is to be traced on innovative activities or on the overall productivity of firms. I argue that, due to the pre-competitive nature of the funded projects under study, it is on the former, and in particular on the R&D input side, that an impact should be searched. In fact, the EPSRC partnerships are aimed at contributing to upstream and basic research that is far from industrial application, hence far from producing R&D outputs. Moreover, I add to the existing empirical evidence on the case of EPSRC-funded partnerships by examining their impact: in fact, while evidence on their determinants, channels, and barriers is vast (see e.g. D'Este and Patel, 2007; D'Este and Fontana, 2007; Ambos et al., 2008; Bruneel et al., 2009, 2010; D'Este and Iammarino, 2010; Bishop et al., 2011; Crespi et al., 2011; D'Este et al., 2012, 2013), it is rather scant as far as their impact on firms is concerned.

VI.3 Organisational-level determinants of academic engagement with industry

The third chapter focuses on the role of academic quality for university engagement with businesses in the form of U-I collaboration in the UK. The aim of this chapter is to investigate the determinants of U-I knowledge transfer activities from the standpoint of academia. In particular, I examine to what extent past research quality, together with other factors, explains the volume of funds that university departments raise from companies when participating to EPSRC funded research collaboration.

I hypothesise that a negative relationship between quality and U-I interaction exists, on the basis of the argument that a relatively low degree of resource availability at lower quality universities may motivate top academics in these schools to seek industry collaboration in order to acquire research funds (Perkmann et al., 2011). Moreover, I expect that this relationship is influenced by academia's past experience in U-I interaction, which I measure with the amount of public funding received by departments for past U-I collaboration.

The empirical analysis is based on data on U-I partnerships funded in the UK by the EPSRC (cfr. supra) combined with information on departments and universities gathered from the 2001 and 2008 UK Research Assessment Exercises (RAE). This is an evaluation exercise carried out approximately every 5 years that provides ratings of research quality to be used by the UK government in funding allocation. In the empirical analysis I estimate a model in which the amount of private funds raised by university departments depends upon a number of department-level characteristics, including past research quality and past experience. Control variables for departments' scientific disciplines and geographical location are also included in the regression analysis in order to capture further patterns in U-I collaboration.

According to the results of the empirical analysis, research quality does not display a neat relationship with the volume of funding for U-I collaboration raised from businesses partners, since a mixture of positive and negative relationships emerge. However, the effect of quality clearly depends on the level of departments' past experience with the funding agency (i.e. past public funding for U-I collaboration). In particular, for low level of past experience, low quality departments receive higher industry funds than top quality ones, whereas the opposite happens for high levels of past experience.

This chapter provides new evidence on U-I knowledge transfer activities and on their value by measuring them with the volume of industry funding rather than simply quantifying them with the number of instances and/or their occurrences. In addition, it focuses on the role of organisation-level determinants for academic engagement by looking at university departments and their characteristics. My results only partly support the argument that there may be a negative relationship between research quality and academic engagement. However, it clearly emerges that quality is interdependent with past experience, since the latter may represent a signal for companies that boosts the effect of quality on the amount of resources raised from companies. This is a relevant result that provides the basis for further research on the role of academia's past experience in U-I interaction. In fact, whereas some evidence exists on the link between universities' past experience and academic engagement (Boardman, 2009; Boardman and Ponomariov, 2009; Bozeman and Gaughan, 2007; Lee and Bozeman, 2005; Link et al., 2007), evidence on past experience as a moderating or enhancing factor of academic quality at department level is rather scant.

VII Concluding remarks

This PhD thesis aims at providing an original and comprehensive analysis of U-I knowledge transfer activities. It is original because it examines in new ways the link between knowledge transfer and private as well as public R&D and innovation activities. It makes use of original data sources, methods and measures, and provides new empirical findings. It is comprehensive because it considers both the determinants and impact of U-I interaction, as well as their geographical dimension, and it looks at these issues both from the standpoint of companies and universities. The three chapters are indeed complementary in that they explore various aspects of the same economic phenomenon.

The findings of the first chapter shows that there is a positive and significant relation between quantity of inventors' patents and the joint use of scientific and market knowledge, whereas the results are slightly less neat as far as patent quality is concerned because a relationship with the joint use of scientific and market knowledge does not always hold. Moreover, the sole use of knowledge from market sources is also significantly related to the quality of inventors in some of the estimations. In addition, mobile inventors benefit more than non-mobile ones from external knowledge. These findings are in line with existing evidence suggesting that external-to-the-firm knowledge is beneficial for firms' patents (Schneider, 2009; Pasquini et al., 2012), and add that quantity as well as quality of industry inventors' patents benefit from the recombination of various sources of external knowledge.

The first chapter has some limitations, which include primarily the fact that by administering the survey questionnaire to patent inventors only, non-patenting inventors have been automatically excluded from the sample. Therefore nothing is known about the knowledge sourcing strategies of the latter group. Moreover, the cross-sectional nature of the data does not allow to properly control for time-invariant factors, and forward citations, although being widely acknowledged as one of the best proxies for patent quality, have some empirical limitations. Nonetheless, this chapter of the thesis offers some contributions to the literature, as previously underlined, but also for policy.

In particular, the evidence of a complementarity relationship between different sources of knowledge for the inventive process supports the well-known argument that knowledge exchange across a wide range of organisations - both academic and non-academic - is beneficial to the innovation performance and the competitiveness of regions. This is particularly true with respect to universities, given that the latter often appears to be among the less important sources of external knowledge, notably if compared to firms (Giuri et al., 2007). In particular, since our study addresses individual innovativeness, it is arguable that knowledge sharing between firms' employees and universities or public research centres, as well as other market actors, require constant effort and investment in establishing relationships. Policies that creates incentives for information and idea sharing with external agents, as well as across firms' departments, could be beneficial to improve the overall organisational innovative process and, in turn, the innovation performance of regions.

The findings of the second chapter of the thesis show that EPSRC U-I collaborations funded between 1998 and 2007 have a positive impact on participating firms' intramural R&D expenditure per employee and share of R&D personnel employed, three years after the beginning of U-I projects. This result is very similar across several matching methods employed for the selection of the control group. Moreover, these findings are in line with those of previous empirical studies (see e.g. Becker and Peters, 2000; Becker, 2003; Lööf and Broström, 2008), as well as with a survey based study of ESPRC collaborations illustrated in Bruneel et al. (2009).

The results of this study should be interpreted with caution due to some empirical limitations. Firstly, this study focuses on the impact of only the first project entered by a firm, hence not considering following projects; besides, it has not investigated whether the results and their magnitude differ across firms and time. Secondly, only UK businesses' engagement in U-I partnerships funded by the EPSRC is considered, but it is well known that firms generally receive funds for research and innovation activities from a wide range of funding agencies. Therefore, the results of the analysis may only provide a snapshot of the whole story.

Nonetheless, the findings of the second chapter contribute to the literature and policy debate. In particular, they support the argument that universities are an integral part of the supply chain to firms and are fundamental for business growth and economic prosperity. This was particularly emphasised in the UK policy discourse from the late 1990s onwards (Lawton Smith and Bagchi-Sen, 2006) and has been recently reaffirmed by the UK Wilson Review of Business-University Collaboration (Wilson, 2012). In particular, our result of a positive effect of U-I projects on firms' R&D employment is in line with Bruneel et al. (2009), who report that firms declared collaborating with university mostly to gain the opportunity to recruit appropriately trained staff. This leads to an important implication for science, technology and innovation policy. It appears that firms go to university for knowledge and technology as well as for highly skilled people. In other words, universities are a 'top locational factor' for firms, not only for accessing information directly, but also - and often mainly - to access scientific and human capital (Lawton Smith, 2007). Therefore, it is important to create comprehensive mechanisms that promote both critical aspects, for instance supporting the use of university research as a means to recruit highly skilled personnel.

Finally, the findings of the third chapter, although not showing a clear picture as far as the relationship between academic quality and U-I collaboration is concerned, highlight the role of university departments' past experience with the funding agency as a driving factor of U-I interaction. In fact, it emerges that past experience, measured with the past volume of EPSRC grants for U-I collaboration, is positively and significantly linked to collaboration with industry, indicating that universities' ability to mobilise public resources represents a signal for businesses.

Although the third chapter has some limitations, including the possibility that some relevant factors remained omitted in the econometric specification and that the measure employed for research quality is an imperfect proxy, it contributes to the literature because it explores new aspects within the debate on U-I links, as underlined in the previous section. Also, its findings suggests that public policy should substantially support university knowledge transfer, especially in light of the increasing costs of research for universities and companies, so to allow the best match of resources by both sides. Moreover, policy-makers could consider a division of labour among universities whereby some specialize in advanced research and others in business engagement (Perkmann et al., 2011).

The three chapters that form this thesis contribute to our understanding of U-I knowledge transfer: to sum up, this work shows that academic knowledge is a fundamental driver of industrial research and innovation, especially when combined with other sources of knowledge; it shows that knowledge transfer between university and companies has a positive impact on firms' R&D inputs, and, finally, that U-I interaction strongly depends upon university's past experience, notably with public agencies, and existing networks of collaboration. Overall, this study highlights the systemic and interactive nature of innovation by showing that interaction among innovators and knowledge producers is a fundamental mechanism to bring research and science forward.

To conclude, this thesis represents a comprehensive and original work, whose limitations pave the way for further research on the topic of U-I knowledge transfer activities. In particular, this thesis focuses on some of the many channels of interaction between academia and businesses. Channels other than patents and U-I collaboration, including both formal (e.g. joint ventures, research contracts, faculty consulting) and informal (e.g. informal meetings, personal exchange) should also be accounted for in empirical analyses aimed at uncovering new aspect of U-I knowledge transfer. Secondly, the adoption of more fine-grained geographical units in some cases would be of help in uncovering new aspects of the role of universities in their territories. This is both the case of publicly supported U-I collaboration in which universities act as 'principal investigator', thus having a key territorial role for the establishment of U-I linkages, and of patent inventors who exploit knowledge sources available outside their company, typically in the local environment.

Chapter 1

The role of scientific and market knowledge in the inventive process: Evidence from a survey of industrial inventors

1.1 Introduction

It is nowadays well established that knowledge that is internal to the firms, though essential, is not sufficient for the creation of innovation. In order to successfully produce innovation and stay competitive on the market, firms have to tap into knowledge that rests outside their boundaries (see e.g. Allen and Cohen, 1969; Allen, 1977; Arora and Gambardella, 1990; Tijssen, 2002; Chesbrough, 2003; Krafft and Quatraro, 2011; Antonelli, 2013). Firms exploit knowledge from different sources, hence combining knowledge from the individuals that are part of the organisation with knowledge from actors that are external to the firm. This is particularly relevant at the local level, since the presence of systemic interactions in the process of generation and diffusion of innovation are nowadays recognised as key drivers of regional technological and economic performance (Iammarino, 2005).

External-to-the-firm knowledge is supplied by a wide range of actors with different characteristics - hence providing different types of knowledge. It is possible to distinguish scientific knowledge, supplied by scientific actors, such as universities and research centres, and technical knowledge, supplied by market actors - and for this reason referred to as market knowledge - such as competitor firms, suppliers and customers (see e.g. Von Hippel, 1988). Scientific knowledge is usually disconnected from the market and its purpose is to foster technological progress (Fleming and Sorenson, 2004), whereas market knowledge is more applicative because it aims at addressing specific users' problems and is, by definition, market-oriented (Cohen et al., 2002). As a consequence, scientific knowledge is seen as fundamental for the idea-generation phase of the innovation process, whereas market knowledge is essential for the technical realisation of a given innovation (see e.g. Utterback, 1971; Hagedoorn, 1993; Tijssen, 2002; Aghion et al., 2008; Frenz and Ietto-Gillies, 2009).

The empirical evidence on the relation between firms' knowledge sourcing strategies and the creation of innovation is vast, though not fully conclusive yet (see e.g. Arora and Gambardella, 1990, 1994; Cassiman and Veugelers, 2006, 2007; Frenz and Ietto-Gillies, 2009). Both complementarity and substitutability between internal and external knowledge, as well as between different types of external knowledge (e.g. scientific and market knowledge), have been documented. This is suggestive of the need to get a closer look at the role of knowledge by exploiting a finer unit of analysis, such as the individuals inside firms. Recently, the empirical literature has looked at the role of knowledge for the individual who is responsible of the innovative process, i.e. the inventor. By exploiting information available from patent documents and surveys of inventors, a number of papers uncovered some of the factors that influence the inventor's patenting activity, including individual characteristics (e.g. education, age, mobility) and knowledge flows (see e.g. Giuri et al., 2007; Hoisl, 2007; Mariani and Romanelli, 2007; Schneider, 2009). However, the relevance of different sources of knowledge and how these combine has been rarely addressed at the micro level of the individual inventor.

This paper focuses on the individuals that are primarily responsible for the inventive activity inside companies, i.e. patent inventors, based on the consideration that innovation is a product of firms and organisations that also requires individual creativity. Patents are commonly recognised as creative output (Huber, 1998), thus they represent the right innovative outcome to look at. The aim of this paper is to show that scientific and market knowledge sources are complementary for the patenting performance of inventors, by testing the hypothesis that the joint use of scientific and market knowledge has a higher impact on the inventor's performance than the separate use of each of the two knowledge sources.

In the empirical analysis, three measures of inventors' performance in terms of quantity and quality of their patents will be estimated as a function of scientific and market knowledge sourcing strategies, controlling for individual-level characteristics as well as patent- and firm- level determinants. This is also known as the productivity (or direct) approach (Cassiman and Veugelers, 2006), which has been widely used in the management literature to analyse the relevance of knowledge flows for firms and, to the best of our knowledge, it is one of the first attempts to apply it at the inventor's level. Ordinary least squares regression with robust standard errors will be employed. Together with the baseline regressions, the breakdown by inventor's job mobility will be shown along with a robustness check.

The novelty of the present study lies, in the first place, in the focus on the individual innovator as unit of analysis, instead of the firm, which is the typical unit of analysis for these types of studies. In addition, the paper exploits an original data source that combines a survey of industrial inventors carried out in three European regions with patent data from the European Patent Office (EPO). Whereas previous literature has mainly relied on proxies for the knowledge linkages of inventors to knowledge sources, the survey data here presented is likely to provide a better indicator since inventors were explicitly asked questions on the use of different knowledge sources in the inventive process.

The remainder of the paper is organised as follows: section 1.2 provides a review of the literature leading to the hypothesis of the paper; in sections 1.3 and 1.4 we present the method and the data used for the empirical analysis; the empirical results are presented and commented in sections 1.5 and 1.6 and finally, the last section concludes the paper by summing up and discussing the empirical findings.

1.2 Literature and hypothesis development

1.2.1 The role of scientific and market knowledge for firms

External knowledge acquisition is necessary for innovation activities carried out by firms, especially in the current context of market globalisation and rapid technological change. Both the early literature on technological change (see e.g. Allen and Cohen, 1969; Allen, 1977) and the more recent studies on the knowledge sourcing strategies of firms (see e.g. Arora and Gambardella, 1990, 1994; Cassiman and Veugelers, 2006, 2007; Frenz and Ietto-Gillies, 2009) assert that firms cannot rely only on their internal resources and have to tap into knowledge outside their boundaries in order to successfully produce innovation.

The evolutionary economics framework of technological change clearly establishes that, due to the systemic and non-linear nature of innovation, interactions between innovative agents represent a key mechanism for the purpose of innovative activities (see e.g. Kline and Rosenberg, 1986; Dosi et al., 1988; Malecki, 1997; Nelson and Winter, 2002). Accordingly, innovation is not only influenced and determined by engineers and scientists working in R&D departments or by the top management inside companies, but also by many sources of information and actors both inside and outside the firm, the latter including firms, knowledge providers such as universities and research centres, public agencies and others.

Moreover, as suggested by a growing body of literature within the economics of innovation, knowledge production can be viewed as the outcome of a recombination process (see e.g. Kauffman, 1993; Weitzman, 1998). Accordingly, innovation results from the combination of new knowledge or from the combination of existing knowledge in new ways. With this respect, knowledge is also viewed as the outcome of a *collective* process of recombination of bits of knowledge that are dispersed among innovative agents (Krafft and Quatraro, 2011), thus supporting the argument that innovation stems from interactions between those agents.

The long-standing debate on the nature of technological change and localised knowledge spillovers arising from that has evolved around the distinction between market knowledge and scientific knowledge. The seminal works of e.g. Griliches (1987); Jaffe (1989); Adams (1990), have uncovered the role of external knowledge from academia - often referred to as scientific knowledge - for innovation activities of firms and, more generally, economic development. For instance, Jaffe (1989) shows that there is a significant effect of university research on local firms' patenting activity. Since then, the literature on firm-university links grew significantly and complemented those seminal studies (see e.g. Mansfield, 1995; Mansfield and Lee, 1996; Cohen et al., 2002), providing evidence of that fact that firms exploit scientific knowledge in order to produce innovations and stay competitive on the market. Also, firms seek and exploit technical knowledge from external agents that are close to the market in order to reduce the uncertainty associated with innovation (Hagedoorn, 1993), that is, to find new ideas, or address technical issues that arise during the innovation process. Close-to-the-market actors include customers, direct competitors and suppliers (see e.g. Von Hippel, 1988). The literature refers to the technical knowledge provided by these actors as market knowledge in order to stress its source, as opposed to scientific knowledge that comes from actors belonging to the scientific community.

The theoretical literature has further underlined how various typologies of knowledge originating from different sources are useful at different stages of the research process. In his seminal work on the process of technological innovation, Utterback (1971) distinguishes three overlapping stages through which an innovation is realised. The first is the idea-generation phase, which results in the origination of a technical proposal or design concept; the second is the problem-solving phase, resulting in an invention or an original technical solution; the third stage consists of the implementation and market introduction, culminating in the diffusion of the innovation.[1] Specifically referring to external knowledge, Utterback states that *'The greater the degree of communication between the firm and its environment at each stage of the process of innovation (...), the more effective the firm will be in generating, developing and implementing new technology'* (Utterback, 1971, pag. 85), thus suggesting that external knowledge is beneficial to the whole innovation process, from the idea-generation phase, to the implementation and commercialisation of an innovation.

[1]The latter is not strictly considered as part of the process of innovation since it partly occurs outside the firm, hence the literature generally considers the first two (overlapping) phases as the main ones (Weck and Blomqvist, 2008).

Similarly, Machlup (1962) provides a very interesting discussion of the flows of ideas through four sequential stages: research, invention, development and application. In this classification, scientific knowledge is listed among the intangible inputs of the initial research and invention stages, as well as the development phase, and technology is among the intangibles that are fundamental to the invention and development stages. Finally, of great importance to the application stage is what Machlup (1962) refers to as 'business acumen' and 'enterprise (venturing)'.

In addition, a recent theoretical contribution investigating the advantages and disadvantages of academic and private research, shows that academia is most useful in the early stages of the research process, whereas the private sector tends be more useful in the later stages (Aghion et al., 2008). The reasons lie behind the different systems of incentives within academia and within firms. Academia, because of its commitment to leaving creative controls in the hands of scientists, can be indispensable for early stage research aimed at fostering new research lines; on the other hand, the private sector's focus on higher payoff activities makes it more useful for later-stage research, aimed at producing profitable innovations and introducing them to the market. Therefore, the literature suggests that external knowledge is fundamental to the innovation process, but also that different sources of knowledge must be accounted for, because potentially having different effects on the different stages of the innovation process.

Besides, the empirical literature shows that firms adopt and use knowledge from different sources, often combining internal and external knowledge acquisition strategies (see e.g. Arora and Gambardella, 1990, 1994; Cockburn and Henderson, 1998). In this respect, the seminal work of Cohen and Levinthal (1990) on the concept of absorptive capacity, defined as the capacity of a firm to recognize, assimilate and exploit external knowledge, particularly stresses the co-existence of different types of knowledge inputs and their contribution to the firm's innovative activities.

Among others, Cassiman and Veugelers (2006) show that internal R&D and external knowledge acquisition are complementary innovation activities, while the same authors finds evidence of substitution effect between embodied and disembodied technology acquisition strategies (Cassiman and Veugelers, 2007). Criscuolo et al. (2005) and Crespi et al. (2008) use firm-level data and estimate a knowledge production function to study the contribution of different knowledge flows to firm-level productivity: the former show that globally engaged firms innovate more thanks to the intra-firm worldwide pool of information as well as from suppliers, customers and universities, whereas the latter particularly stress the importance of clients, among the knowledge flows. Although existing evidence is mixed, it seems clear that external knowledge contributes to the innovation process and that different typologies of knowledge flowing from a wide range of different actors matter.

1.2.2 The role of scientific and market knowledge for inventors

The existing evidence on the the role of external knowledge for innovation mainly takes the firm and its innovative activities (e.g. commercial activities, inventions, sales of innovative products) as the unit of analysis. However, the attention has recently moved down to a finer level of analysis, that is the individual inventor inside the firm (see e.g. Giuri et al., 2007; Hoisl, 2007; Mariani and Romanelli, 2007; Weck and Blomqvist, 2008; Schneider, 2009; Pasquini et al., 2012). The interest in the inventor as the main unit of analysis is justified by the fact that innovation is not simply the product of firms and organisations. It ultimately requires individual effort and creativity and patents are, indeed, commonly recognised as creative output (Huber, 1998). Therefore, individual inventors arguably represent an interesting unit of observation to consider in order to inquire into firms' innovation activities. Moreover, the empirical evidence about university inventors is vast, partly because of a large amount of information publicly available, whereas evidence on industrial inventors is rather limited and not conclusive yet.

Extant research confirms that patent productivity among private inventors is skewed, similarly to that of academic inventors - i.e. few inventors produce a high number of innovations whereas the vast majority display a low invention rate - but, because of the lack of information at individual level, it is hard to identify the reasons behind this behaviour (Mariani and

Romanelli, 2007; Menon, 2011). Furthermore, it has been shown that both inventor's factors and characteristics of the employers affect the inventor's performance (Giuri et al., 2007).

As mentioned above, more recently there have been attempts to address the role of knowledge flows for inventors. Previous studies show that scientific sources of knowledge are often the least important for inventors (and more generally, for firms) and market sources of knowledge are instead the most important ones (Eurostat, 2007; Giuri et al., 2007). This is not surprising, since the distance between purely scientific knowledge and technical knowledge stemming from market channels is quite large. Notwithstanding, only recently the interdependence of the two for the inventive process has been investigated in the literature. On the one hand, it has been shown that scientific and market sources of knowledge display a subadditive relationship for the monetary value of the inventions (Schneider, 2009). On the other hand, it has been uncovered a positive and significant contribution of external-to-the-firm knowledge to the probability that a patent is commercialised (Pasquini et al., 2012). Moreover, a qualitative case study on the inter-organisational relationships developed by inventors within a company, shows that patent competitiveness benefits more from buyer-seller relationships than from R&D consortia (Weck and Blomqvist, 2008).

The evidence on the role of knowledge for industrial inventors and their performance is, therefore, still scant and not yet conclusive. In addition, the existing studies, though accounting for the inventors' use of knowledge, exploits patents as the ultimate outcome measure, instead of the inventor. The present study intends to fill these gaps by focusing on the relationship between industrial inventors' knowledge sourcing strategy and their patenting activity. In order to shed new light on the role of different knowledge sourcing strategies for inventors' performance, the research question that will be addressed in this paper is *'Do industrial inventors that use various sources of knowledge in their inventive activity display higher performances that those who do not?'*. In other words, we will ask whether inventors who combine the use of both scientific and market sources of knowledge display a higher number of patents and produce higher quality inventions than inventors who use only one or none of them.

As previous studies suggest, scientific and market knowledge produce different effects on the inventive process, due to their very different nature. Scientific knowledge is usually disconnected from the market and its purpose is to foster technological progress (Fleming and Sorenson, 2004), whereas market knowledge is more applicative, aims at addressing specific users' problems and is, by definition, market-oriented (Cohen et al., 2002). These differences are evocative of very different impacts on the inventors' innovation activity, suggesting that inventors who merely use scientific knowledge might have radical ideas but create innovations that are far from the market or hard to commercialise, while inventors who prefer market knowledge might not focus on breakthrough innovation but instead create close-to-the-market and more profitable innovations. In reality, inventors often combine these sources of knowledge, which suggests that there could be a complementarity relationship between the two and this might have consequences on the inventors' performance.

In line with the discussion proposed earlier in this paper on how knowledge originating from different sources is useful at different stages of the research process (Machlup, 1962; Utterback, 1971; Aghion et al., 2008), we expect that inventors drawing upon a higher number of external knowledge sources display a better performance than inventors who do not. Hence, we argue that knowledge produced in and sourced from science-related channels (university and public research centres) display a complementarity relationship with knowledge from market-related actors (suppliers, customers, competitors, consultants) for the inventors' performance in terms of patent count and patent quality. The argument is that, by combining these two types of knowledge, inventors exploit different characteristics of the latter that fulfill different needs throughout the inventive process: in other words, inventors would be merging the technological and innovative potential that derives from scientific knowledge with the market potential that derives from market knowledge (Pasquini et al., 2012). Hence, we put forward the following hypothesis:

Hp: The joint use of scientific knowledge and market knowledge has a higher impact on the inventors' performance than the separate use of each of the two knowledge sources.

In order to test this hypothesis, the inventors' knowledge sourcing strategies will be measured and used as explanatory variables for the inventors' patenting activity, by exploiting the so-called productivity approach (Cassiman and Veugelers, 2006). In the next section the data sources are first described, followed by the empirical strategy and the construction of the variables employed in the analysis, along with their descriptive statistics.

1.3 Data and method

1.3.1 The Survey of inventors and the EPO data

This paper makes use of a survey of industrial inventors that has been carried out under the umbrella of a European Commission Seventh Framework Program funded project (PICK-ME[2]), with the aim of exploring the inventive process inside regions. The motivations for this survey primarily stem from the need to shed new light on the the drivers of inventive activities inside companies within territories. In fact, over the last two decades it became increasingly accepted in economic literature as well among policy makers that countries' competitiveness and innovative performances are especially determined at the local levels, primarily at the regional level (OECD, 2001; Doloreux and Parto, 2004). Since then, it has been extensively documented that the localised network of actors and institutions in the public and private sectors facilitates innovation (Iammarino, 2005).

Indeed, as underlined in the introductory chapter of the thesis, the theoretical approaches that developed from the 1980s onwards on the basis of the interactive and non-linear definition innovation - e.g. Systems of Innovation and Triple Helix Models (see e.g. Freeman, 1987; Lundvall, 1988, 1992; Nelson, 1993; Nelson and Rosenberg, 1993; Edquist, 1997; Leydesdorff and Etzkowitz, 1996, 1998; Etzkowitz and Leydesdorff, 1997, 2000) - were soon extended to the regional level. This is particularly the case of Regional Systems of Innovation (see e.g. Autio, 1998; Braczyk et al., 1998; Cooke, 2001; Asheim and Isaksen, 2002; Asheim et al., 2011), defined as networks of actors and institutions in the public and private sectors whose activities

[2]Grant agreement n. SSH-CT-2010-266959.

and interactions generate and diffuse new technologies, within and outside the region.

The survey of inventors here presented was administered between 2011 and 2012 in three European regions, namely, Catalonia (Spain), East and West Midlands (United Kingdom) and Piedmont (Italy), with the objective of obtaining new insights about the demand of knowledge expressed by the actors directly involved in the innovative process inside their regional systems of innovation. In addition, the survey aimed at gathering individual-level information that are not usually available in patent documents, such as their age, gender, education and occupation. In the empirical analysis of this paper, the final dataset consists of the survey data combined with patent data from the European Patent Office (EPO).

The survey questionnaire was sent to industrial inventors who filed one or more patent applications between 2000 and 2006 and whose residential address was in one of those regions. Information on the inventors' names and home address was extracted from the CRIOS-Bocconi Patstat database.[3]

The selection of regions was based on a number of factors and comparability issues. On the one hand, the aim was to choose non-core regional innovation systems, particularly non-capital regions which, because of the presence of national research institutions and/or other core research organisations, would display peculiar characteristics in terms of knowledge linkages. Indeed, according to the 2012 and 2009 European Commission Regional Innovation Scoreboards, none of the regions in our sample was part of the group showing the highest innovation performance (i.e. 'high innovators' or 'innovation leaders') in the years pre-2006.[4] On the other hand, regions displaying similar innovation performances were to be chosen; in fact, as of 2006, the three regions were categorised in the same group in terms of innovation performance, namely, 'average to

[3]The EPO Patstat (PATent STATistical) database is a patent statistics raw database, held by the EPO and developed in cooperation with the World Intellectual Property Organisation (WIPO), the OECD and Eurostat. A clean version of the raw data was provided by CRIOS-Bocconi (`http://ricercaweb.unibocconi.it/criospatstatdb/`).

[4]`http://ec.europa.eu/enterprise/policies/innovation/files/ris-2012_en.pdf`
`http://ec.europa.eu/enterprise/policies/innovation/files/ris-2009_en.pdf`

medium-high innovators' or 'innovation followers' on the basis of several indicators. The latter include regional enabling factors (education level and public R&D expenditure), firm activities (business investments in R&D, knowledge linkages in entrepreneurship, intellectual assets), and outputs (product/process/organisational business innovation, innovative sales, R&D employment). Innovation followers are characterised by a balanced performance structure in terms of all indicators.[5]

The survey includes a question on the use of different sources of knowledge, split into internal sources (colleagues inside the firm and other business unites/departments) and external sources, i.e. customers, competitors, suppliers, consultancy, universities and public research centres. The question asks to the inventor to rank the relevance of each source from 0 (not used) to 4 (very important). The sample of respondents includes 225 inventors from Catalonia (response rate 14%), 117 inventors from the Midlands (response rate 13%) and 533 inventors from Piedmont (response rate 45%). These have been matched to the CRIOS-Bocconi Patstat database via inventor's identifier. It has been possible to retrieve all patent information for each inventor, including the number of patent applications, the status of each application - whether a patent has been granted or not -, patent technological classes (reclassified into 7 macro-classes), number of forward citations of each patent, assignee of the patents (i.e. the owner).

1.3.2 Empirical strategy

The estimation strategy follows the so-called productivity (or direct) approach (Cassiman and Veugelers, 2006), in which measures of inventors' patenting activity are estimated as a function of the inventors' knowledge sourcing strategies, as well as a number of control variables to account for individual characteristics, patent features and firm factors. The knowledge sourcing strategies have been created as exclusive dummies that indicate whether inventors declared using only scientific knowledge or only market knowledge, or both, or none of them. The model will be estimated with ordinary least squared regressions with robust standard errors, to account for potential heteroskedasticity of the error terms (Angrist and Pischke, 2008).

[5]Ibid.

In order to test our hypothesis we estimate a model in which the dependent variables (Y_i) - fully explained in the next section - *lNpat* (log of number of patent applications per inventor), *Meanfcc* (average quality of inventions per inventor) and *Maxfcc* (quality of the best inventions per inventor), are regressed on the inventors' knowledge strategies plus a vector of control variables (X_i):

$$Y_i = \alpha + \beta_1 scionly_i + \beta_2 mktonly_i + \beta_3 scimkt_i + \gamma X_i + \epsilon_i \tag{1.1}$$

Where (1) *scionly* is a dummy variable taking value 1 for inventors who use only scientific knowledge, (2) *mktonly* is a dummy variable taking value 1 for inventors who use only market knowledge, (3) *scimkt* is a dummy variable taking value 1 for inventors who use both scientific and market knowledge, and (4) *noscimkt*, excluded from the regression to avoid multicollinearity, takes value 1 for inventors who do not use any external source of knowledge.

The econometric analysis will be performed on the full sample as well as on the subsamples of mobile and non-mobile inventors. In addition, a robustness check for the quality measure will be carried out, in which a weighted measure of quality will be used.

1.4 Measures

1.4.1 Dependent variables

1.4.1.1 Inventors' patent count

The variables of interests for the analysis are quantity and quality of inventions at inventor's level. In the patent literature, patent count is usually used as a measure of inventor's production of patents (see e.g. Hoisl, 2007; Mariani and Romanelli, 2007). Patents suffer from one limitation with this respect, that is, they do not capture non-patented inventions.[6]

[6]More generally, the measurement of innovation using patent data suffers from at least three limitations, as pointed out by De Rassenfosse et al. (2014): firstly, not all inventions are patentable and not all patentable inventions are patented; secondly, the value of patents varies widely and the majority of patents is worthless; thirdly, the common practice to count patents at a single patent office often results in selection bias, since applicants have the option of filing patents anywhere in the world. The latter may particularly apply to

By accounting only for inventions that successfully reached the market, one neglects the relevance of other inventions whose patent applications are still under evaluation by the EPO, but that nonetheless represent the outcome of innovative activity. Since the EPO dataset keeps track of all patent applications, it is possible to mitigate this bias by taking into account both granted patent and patent applications. The latter capture inventions that have the potential to be patented and thus have been sent out for application at the EPO, but, at present, have not been granted a patent (yet). Therefore, we include in the patent count measure (*Npat*, used in log in the regression) both patent applications and granted patents between 2000 and 2006.

Due to the short time span, only a truncated measure of inventors' patent count can be observed. As a consequence, we would be treating inventors who started patenting before 2000 the same as inventors who start later or after 2000, hence not taking into account the past patenting activity (if any). This bias, known as truncation bias, can be mitigated by controlling for the age of inventors and for the year in which each inventor enters the sample. In particular, the aim of the latter control is to compare inventors with those that are part of the same cohort, namely those who 'start' patenting in the same year.

1.4.1.2 Quality of inventions

The second variable of interest is the quality of each inventor's patents and is measured with the forward citations received by each patent. Each patent has to cite the prior art on which it builds on, and the forward citations count is the number of times the patent is cited by other patents after it has been granted.[7] Previous empirical evidence shows that forward citations are highly correlated with the value of inventions (see e.g. Trajtenberg, 1990; Harhoff et al., 1999; Hall et al., 2001; Lanjouw and Schankerman, 2004; Hall et al., 2005). Therefore, the more forward citations a patent receives, the higher is the quality of the patent. This relationship relies on

our sample of EPO patents, since in Europe two overlapping patent offices coexist: applicants may file patents directly at their national patent office or they may take the European route by filing patents at the European Patent Office (EPO). Moreover, they may file their patents at other jurisdictions, including the World Intellectual Property Office (WIPO), the US Patent and Trademark Office (USPTO) and the Japan Patent Office (JPO).

[7] Forward citations differ from backward citations, which are the past patents cited in patent applications.

the assumption that a highly cited patent represents an important invention that will constitute relevant prior art for future patents. Although forward citations may represent an imperfect measure, due to a number of drawbacks including truncation, self-citations, variation across technological classes (Hall et al., 2001), they are still considered a valuable proxy for the quality of a given patent because they mirror its technological value (Nagaoka et al., 2010).

Based on the number of forward citations received by each inventor's patents, two measures of quality are created. Following inter alia Hoisl (2007) and Mariani and Romanelli (2007), in order to measure the patent quality at inventor's level, we use the average number of forward citations across each inventor's patent during 2000-2006 and the highest number of forward citations among each inventor's patents in the same period. The former (*Meanfcc*) measures the average quality of inventors, whereas the second (*Maxfcc*) accounts for the 'best' invention among those produced by each inventor and thus measures the highest technological success of the inventor during the time span under consideration.[8]

Table 1.1 summarises the descriptive statistics of the dependent variables in the whole sample as well as split by region of residence. The variables are *Npat* (number of patent applications)[9], *Meanfcc* (average number of forward citations) and *Maxfcc* (highest number of forward citations).

The average number of patent applications per head in the whole sample of 875 inventors is 1.82. In line with previous evidence (Giuri et al., 2007; Menon, 2011), the variable is highly skewed, since the maximum number of patent applications per head is 27. The histogram in figure 1.1 shows the distribution of this variable: 67% of inventors applied for a patent only once between 2000 and 2006, while only 6% of the sample

[8]Patent citations take time and only a small number of citations occur for younger patents. In order to deal with this problem, usually only the number of forward citations received within 5 years (or so) from the publication is taken into account, based on the evidence that more than 50% of citations received occur within this period (Nagaoka et al., 2010). However, because of the characteristics of our data, applying this correction would lead to a very small sample of observations.

[9]This variable will be used in log in the regression. It is reported in levels in in order to provide an easily readable measure of how many patents each inventor produces.

did it more than five times. From these figures it could be argued that the majority of inventors in the sample are occasional inventors, because patenting only once. However, because of the short time span under analysis, this hypothesis cannot be tested. The average number of patent applications in Catalonia and the Midlands is the same (1.57) and below the average, while it is above the average (1.98) in Piedmont.

Looking at the quality measures, the average number of forward citations across each inventor's patents is 2.21 and, similarly to the absolute number of patent applications, this variable is highly skewed. Turning on the inventions with the highest number of citations, 3.21 is the average, meaning that, on average, the best invention has been cited 3.21 times by other patents. However, this figure goes up to 114, hence showing that there is a high variation across inventors. Finally, Piedmont's inventors show higher performances than Catalonia and the Midlands' inventors in terms of both mean citations and highest number of citations, as it was the case for the number of patents applications.

The differences in the performance of inventors located in Piedmont with respect to those located in Catalonia and the Midlands confirms overall differentials in innovation performance among these regions. As of 2007, EPO patent applications per billion of regional gross domestic product amount to 0.53 in Piedmont, 0.46 in Catalonia, and 0.49 and 0.48 in East and West Midlands respectively.[10]

1.4.2 Explanatory variables

1.4.2.1 Knowledge sources

In order to build the independent variables we use one question of the survey that asks to the inventors to rank the importance of a number of sources of knowledge, from 0 (not applicable because not used) to 4 (very important). The question specifically states '*Please indicate whether interactions with any of the following actors have been important to get relevant information and knowledge for the work related to your patenting activity during the period 2000-2006*'. Both internal and external-to-the-firm actors are listed.

[10] http://ec.europa.eu/enterprise/policies/innovation/files/ris-2012_en.pdf

However, the focus of this paper is on the role of external organisations, which are (as listed in the question): suppliers, clients and customers, competitors and consultancy/private R&D laboratories; universities and public research centres (see table 1.2).

Firstly, from the respondents' answers, we build a measure of the use of each knowledge source, hence six dummies indicating that the inventor used each given source if she answered 1 to 4, and not used it if she answered 0. In order to create the scientific and market knowledge measures, universities and public research centres are aggregated under the category 'scientific knowledge' and all the others under the category 'market knowledge'. Therefore, the dummy variable that indicates whether the inventor used scientific knowledge (*SCIKnow*) has value 1 if she used either knowledge from universities or from public research centres (or both), while the variable indicating the use of market knowledge (*MKTKnow*) takes value 1 if the inventor used at least one (or more) of the market sources. Table 1.3 shows the descriptive statistics of each knowledge source, as well as their aggregation into scientific and market sources. The share of inventors who used at least one scientific source is 62% and the correlation between the use of universities and that of public research centres is quite high, 0.62, supporting their aggregation. Almost every inventor used at least one of the market sources (91%), although it ranges from 54% of inventors exploiting knowledge from consultants to 71% of inventors using knowledge from clients and customers. As for the correlation among them, it is worth noticing that the figures are all above 0.30, with the highest being the correlation between knowledge from suppliers and knowledge from customers (0.43). Finally, the correlation between scientific knowledge and market knowledge is 0.2 and it is significant at the 5% level, suggesting that there is a positive link between the two.

1.4.2.2 Inventors' knowledge sourcing strategies

In order to apply our chosen methodology, inventors' knowledge sourcing strategies have been derived from the above mentioned knowledge categories for scientific and market sources. Hence, we create the following mutually exclusive dummies:

1. *scionly*: taking value 1 for inventors who use only scientific knowledge (*SCIKnow*=1 and *MKTKnow*=0);

2. *mktonly*: taking value 1 for inventors who use only market knowledge (*SCIKnow*=0 and *MKTKnow*=1);

3. *scimkt*: taking value 1 for inventors who use both scientific and market knowledge (*SCIKnow*=1 and *MKTKnow*=1);

4. *noscimkt*: taking value 1 for inventors who use none of them (*SCIKnow*=0 and *MKTKnow*=0).

By using this approach we intend to compare the performance of inventors who used both scientific and market knowledge, with that of inventors who used only scientific or market knowledge or none of them. Table 1.4 shows the frequencies of the exclusive dummies along with their means and correlation with the dependent variables, for each sub-group of inventors.

The most widespread strategy is that of both using scientific and market knowledge sources (59% of inventors), followed by the use of market sources only (31.25%). Very few inventors used only scientific sources and none of the knowledge sources (3.06% and 6.65% respectively). The breakdown of the dependent variables by knowledge sourcing strategy shows that inventors using both scientific and market knowledge have the highest performance in terms of number of patent applications (*Npat*) (1.98), and best invention (*Maxfcc*) (3.51). Inventors who only use market sources have the highest number of average citations across patents (2.42), therefore the highest average quality of inventions (*Meanfcc*). The groups of inventors using only scientific knowledge and none of the sources have the lowest performance. These figures, although only descriptive, seems to tell that inventors who combine the two sources of knowledge benefit more than inventors who do not combine them, therefore suggesting the existence of a complementarity relationship between scientific and market knowledge. The correlation values shows that there is a positive - although weak - correlation between the joint use of scientific and market knowledge and the performance measures. Inventors' quality is also positively correlated with the use of market knowledge.

1.4.3 Control variables

Control variables have been created at inventors' level. These are: individual characteristics derived from the survey, patent features extracted from the patent data, and employer information provided by the inventors in the survey responses. As for individual characteristics, we control for inventor's gender, age and age squared, assuming that age might display a quadratic relationship with inventor's performance, and education level, by using 4 dummies indicating the highest education level attained by the inventors (Secondary school degree, Bachelor degree, Master degree, Doctoral studies). Furthermore, from the survey it was possible to extract information on inventors' mobility between jobs and job position inside the firm (e.g. R&D department, sales, marketing, etc.). We also control for whether the inventor retired during the period under analysis. Finally, dummies for inventors' region of residence are introduced. These allow to control for region specific factors that may affect inventors' patenting performance, including the presence and reputation of local universities and research centers, as well as local government institutions and the regional industrial structure. As for patent characteristics, we control for whether inventors ever realised patents jointly with other inventors, and for the share of foreign-owned patents, calculated as the share of patents whose owner is not located in the inventors' country of residence. Both variables measures the inventors 'openness' towards external knowledge (Hoisl, 2007).

In order to mitigate the truncation bias arising from using a short time span, we control for the year in which each inventor enters the sample. To do so we use the year indicated in the priority date of the first patent application (for each inventor) during the time frame under investigation. The priority date is the date of filing of an earlier (or the first) application for which priority is claimed. The aim of this control is to compare inventors that are part of the same cohort, namely those who start patenting in the same year. Finally, in order to account for variation across technological classes, we control for seven patent technological macro classes, following the reclassification of the International Patent Classification system developed by the french Observatoire des Sciences et des Techniques (OST). These are Electrical Engineering and Electronics (ost1), Instruments (ost2), Chemicals and Materials (ost3), Pharmaceuticals and Biotechnology (ost4), Industrial Processes (ost5), Mechanical Engineering, Machines and Transport (ost6), and Civil Engineering and Consumer goods (ost7).

As for employer's characteristics, we control for the international exposure of the most recent employer listed by the inventor, with a dummy that equals one if it is a multinational company.[11] This variable accounts for firms' 'openness', assuming that more internationalised firms also tend to co-operate with external actors and hence widen the pool of knowledge where inventors can tap into. We also include firm fixed effects to control for the fact that some firms employ more than one inventor in our sample. A set of firm dummies has been hence created, including both those that employ only one inventor and those that employ more than one of them. By including these dummies, we aim at isolating unobservable drivers of inventors' performance that are explained by employers' characteristics.

The average age of inventors in the sample (table 1.5[12]) is 44 years old, 40% of them have a Bachelor Degree, while 18% also hold a PhD. Quite a large share of inventors (68%) changed job at least once during the period 2000-2006 and around 44% of the whole sample work in R&D-related job positions inside the firm. As for their patenting behaviour, most of them (70%) have co-invented at least one of their patents. On average, 16% of an inventor's patents is owned by an organisation located abroad with respect to the inventor's country of residence. Furthermore, the majority of inventors apply for patents classified in the technological classes of mechanical engineering (37%) and electrical engineering (28%), while pharmaceutical has the lowest frequency of patents applied for (11%). Finally, almost half of the inventors are employed by a multinational firm and around half of the inventors work in a firm where at least another inventor of the sample is employed too. The cross tabulation of the variables *mne* and *co-employment* shows that 38% of the inventors that are co-workers are employed by a multinational company.

[11]This variable has been created by checking companies' webpages and/or their accounts. For every company, we checked whether it has any facilities and other assets in at least one country other than its home country.

[12]The figures in table 1.5 are based on a sample of 710 observations, corresponding to the sample used in the regressions. Descriptive statistics for the full sample are provided in table 1.12 in the Appendix. In addition, the full list of variables used in the regression analysis is provided in the Appendix as well (table 1.13).

1.5 Results

1.5.1 Inventors' performance: quantity of patents

Table 1.6 shows the results of the OLS regression of inventors' patent count, measured as the number of patent applications filed between 2000 and 2006 (in log).[13] The joint use of scientific and market knowledge (*scimkt*) is always positive and significant as well as stable in magnitude across different estimations, while the sole use of scientific (*scionly*) or market (*mktonly*) knowledge is never significant. This indicates that inventors who jointly use knowledge from market sources and from university or research centres have a higher number of patent applications than those who do not use any of them (the baseline is *noscimkt*) as well as than those who use only market or scientific knowledge. This suggests that, as hypothesised, inventors performing better are those who combine into their inventions the technological and scientific potential of knowledge sourced from university and research centres with the market potential of knowledge coming from market actors.

Along with inventors' knowledge sourcing strategies, their individual characteristics are first introduced (column (1)), followed by dummies for the region of residence, job characteristics and year dummies (column (2)); then patent features are added (column (3)) and finally firm factors - dummy for MNEs and firm dummies - are controlled for (column (4)). The coefficient of age has the expected positive sign and is significant at 10% level, showing that older inventors have more patents, but this disappears once we introduce year dummies to control for when inventors started patenting. Inventors with a PhD degree patent less (coefficient negative and significant at 5% level in column (1)) than inventors who just hold a high school diploma (baseline), which could be explained by the fact that the latter group enters the job market right after secondary education (or most likely after the university degree), hence start patenting earlier, but this relationship disappears once other factors are controlled for.

[13] We report the results of this model estimated through a count data regression (table 1.14 in the Appendix). Due to over-dispersion of the variable $Npat$ (mean 1.82 and variance 4.14) we estimate a negative binomial regression: the results are very similar to those obtained via OLS, particularly with respect to the relationship between *scimkt* and the number of patents per inventor, with the only exception of Model (4), where the coefficient of *scimkt* is not significant.

The dummy for co-inventorship is always significant, showing that inventors who cooperate with other inventors (which are in fact the vast majority - 70% of the sample) are also more productive. Finally, the region dummies tell that, with respect to the baseline category (inventors from Piedmont), Catalan inventors display a significantly lower performance in every estimated model, except for the last one. However, this is not the case for inventors from the Midlands. Therefore, ceteris paribus, inventors from Piedmont display the highest productivity in terms of number of patent applications.

The R squared in column (4) rises up to 0.7 once the firm dummies are introduced in the regression. These help controlling for firms' unobservable factors that it is not otherwise possible to control for, and show that employers' characteristics might play a role in individual decisions. Hence, it can be argued that inventors' production of patents is related to some extent to firms' decisions aside individuals' ones. However, it should be noted that the joint use of scientific and market knowledge - although less significant than in the other estimations - still represents a driving factor of patenting activity, with a coefficient for *scimkt* of 0.198, corresponding to an increase in the number of patents per inventor by 21.8%.[14] In conclusion, it can be said that the joint use of scientific knowledge and market knowledge systematically shows a positive relationship with the number of inventors' patent applications, and that it is also quite stable when controlling for individual characteristics, patent features and firm factors.

1.5.2 Inventors' performance: average quality and top invention

Table 1.7 displays the OLS regression results for inventors' quality, measured as the average number of citations across each inventor's patents - *Meanfcc* - (columns (1) to (4)) and the highest number of citations per patent obtained by each inventor - *Maxfcc* - (column (5) to (8)). The coefficient for the joint use of scientific and market knowledge (*scimkt*) is positive and significant until we do not control for employers' factors. In fact, the

[14]The interpretation of the estimated coefficient of a dummy variable in a log-linear regression is calculated by taking the anti-log of the coefficient and subtracting 1 to that, so to find the estimated % change in the outcome variable (Halvorsen and Palmquist, 1980).

introduction of a control for MNEs and the firm dummies soaks up part of the explanatory power (apart for the coefficient for *co-inventor* that is still positively and significantly correlated to the highest number of citations received). Therefore, once controlling for firm factors, the hypothesis of complementarity between scientific and market sources seems to have no support. In addition, the coefficient for *scimkt* is very similar to that for *mktonly*, indicating that the joint use of different knowledge sources is not systematically better than the separate use of market knowledge for the quality of inventions. This is suggestive of the fact that inventors' interactions with market actors (i.e. other firms mainly) only may have a positive impact on the quality of the inventions, whereas this was not the case for the quantity of patents applied for.

As for inventors' characteristics, it is worth noticing the existence of an inverted-U shape relationship between age of inventors and quality of their inventions: in columns (1) and (5) the coefficient of *age* is positive and significant and that of age squared (*agesq*) is negative and significant, both at 5% level, but it loses significance once other factors are controlled for. As the inventors grow older, they tend to produce inventions of higher quality, but after a threshold the relationship becomes negative, meaning that after a certain age (around 45 years old for both average quality and best invention), the quality of inventions decreases. This is in line with previous evidence showing that scientists' productivity may first increase and then decline with age (Mariani and Romanelli, 2007), following scientists' career path.

As expected, inventors working in an R&D department, rather than in other departments (e.g. marketing or sales), produce inventions of higher quality, since the coefficient of *R&Djob* is positive and significant in model (2), (3), (6) and (7). Similarly to the case of inventors' patent count, the dummy variable for co-inventors has a positive and significant coefficient in almost every model, but it is particularly important for the quality of the best invention. This could be explained by the fact that working in teams of inventors, rather than working alone, increases the chances to develop a technological hit as well as the quality of the latter. Finally, the region dummies are never significant, thus nothing can be argued about differentials in the quality of inventions of inventors located in different regions.

The knowledge variables lose any significance in models (4) and (8) once firm factors are accounted for, which brings to the argument that there might be some firms' unobservable factors that drive inventors' performance, as well as their decision to use any external source of knowledge. To sum up, there is a positive relationship between the joint use of different sources of knowledge and inventor's quality but this is less neat than it was for inventors' number of patents. This is partly because the use of knowledge from market channels is almost equally relevant for the quality of inventions, and it is particularly true when employers' factors are accounted for.

1.5.3 Inventors' mobility and the use of scientific and market knowledge

The literature on inventors' performance has underlined that one of the influencing factors of inventors' patenting activity is their job mobility pattern. Trajtenberg (2005) is among the first scholars who studied the link between mobility and productivity and shows that the former has a positive impact on innovative output. In particular, mobile inventors have more valuable patents, that is, more cited patents. Hoisl (2007) studies a sample of German inventors and shows that those who change job are more productive than those who do not, although increases in productivity decrease the probability of observing a move. Since 67.4% of inventors in our sample changed job at least once during the years 2000-06, it is interesting to look for any heterogeneity of the results across the two groups of mobile and non-mobile inventors. In order to do so, the sample of inventors is split into mobile and non-mobile inventors, by exploiting the dummy *jobmobility*, that has been constructed from the information provided by the survey respondents. Mobile inventors are those who moved from one job to another between 2000 and 2006. Non-mobile inventors are those who did not change job in 2000-2006 (but may have done so earlier or later). The decision to observe mobility in this time frame is motivated by the fact that the key variables of interests are observed during that time period.

Table 1.8 shows the OLS results obtained by regressing inventors' patent count (*lNpat*) against their knowledge sourcing strategies, their individual characteristics and patent factors, for the subsample of mobile inventors (67% of the sample) in the left panel and for non-mobile inventors (33% of the sample) in the right panel. Table 1.9 displays the same regressions results but on the measures of quality, both average forward citations (*Meanfcc*) and highest number of citations (*Maxfcc*). In both tables only the coefficients for the knowledge sourcing strategies are reported.[15]

While there is not a striking difference between mobile and non-mobile inventors in terms of their number of patent applications (the coefficients for *scimkt* are very similar, though slightly higher for non-mobile inventors), the same cannot be said for the quality of their inventions, which instead displays some variation across the two sub-samples. In particular, the coefficients for the knowledge sourcing strategies in the sub-sample of non-mobile inventors are never significant. If we consider job mobility as a proxy for openness, this result can be interpreted as that non-mobile inventors are less open to external knowledge and when they use it, this does not impact the quality of their inventions.

Instead, the joint use of scientific and market knowledge is positively and significantly related to both average quality of inventions and quality of the best inventions for mobile inventors. Mobile inventors may have developed connections with other (external) organisations due to their job experience and have, hence, the ability to exploit external knowledge, which, in turns improves the quality of their inventions.

1.6 Robustness check for the quality of inventors

The empirical results discussed so far suggest that inventors' quality display more variation than quantity with respect to the use of external-to-the-firm sources of knowledge. It is thus worth it to check whether the results hold, by carrying out a robustness check. As mentioned before, the employment of the number of forward citations received by a patent, though a widely used proxy for inventors and inventions' quality, raises a number of concerns with respect to its reliability. Among other things,

[15] In tables 1.8 and 1.9 firm dummies are never introduced due to the small number of observations, especially in the sub-sample of non-mobile inventors.

different technological classes might display quite large differences in terms of number of inventions and number of forward citations received by patents (see e.g. Hall et al., 2001). As shown in figure 1.2, there is quite a high variation in the total number of forward citations per technological class, ranging from around 4000 citations received by patents classified into civil engineering to more than 9000 citations received by patents into mechanical engineering. The mean value (number of total citations weighted for the number of patents) varies much less, with the most cited patents into chemicals (3) and the lowest into civil engineering (1.6). From figure 1.3 it is possible to notice that there is even more variation across both regions and technological classes if we consider the mean number of forward citations. In fact, it appears that citations to patents, especially in electrical engineering (ost1), instruments (ost2), chemicals (ost3) and pharmaceuticals (ost4), display quite a high variation across regions, with the Midlands having the highest figures. As far as intra-regional patterns are concerned, Catalonia and Piedmont display rather homogeneous figures, whereas the Midlands show a bias towards the above mentioned technological classes.

While differences between regions clearly depend on the sectoral composition of regions, it is hard to say whether differences across technological classes just depend on different citations practices, hence are somehow artifactual, or reflect a 'real' phenomenon. In particular, these can be due to some technological areas being more innovative and characterised by innovation breakthroughs - hence by a higher rate of patenting and more citations - whereas some others are less innovative and mainly produce incremental innovation - hence less patenting activity and lower citations (Hall et al., 2001). When such differences exist, the use of the mean number of citations across each inventor's patent might not capture this heterogeneity.

Therefore, as a robustness check for the estimation of inventor's quality, we employ a different dependent variable with the dual aim of correcting for the potential bias and checking whether the main results are confirmed. The new dependent variable is a weighted average of forward citations at inventor level in which the number of citations received by each patent is firstly weighted for the average number of citations received by all patents in the same technological class (i.e.: for each patent, its weighted quality is calculated). The first step is done by region of residence of the inventor, so that each patent is compared to the average number of forward citations received by patents in the same class within the same region.[16] This is done to account for variation across both regions and technological classes and follows the rationale proposed by Hall et al. (2001), according to which, in order to remove all sources of variation in citation intensities, it is necessary to re-scale citation counts by dividing them for the average citation count of a group of patents to which the patent of interest belongs.[17]

Secondly, the weighted quality of each patent is used to create the measure of inventor quality, by calculating the mean across each inventor's patents, similarly to what has been done for the variable *Meanfcc*.[18] Table 1.10 displays the mean values of the newly created variable *Meanfcc_weighted*: the figures show that there is still some variation across regions, but less so across technological classes (within regions), which is what the new measure was thought for.[19]

The econometric analysis follows the same model employed in the previous estimations: inventors' quality is estimated as a function of the three knowledge sourcing strategies plus the usual vector of control variables. The OLS results in table 1.11 shows that the findings are generally consistent with the main estimation in table 1.7, hence partially confirming the positive relationship between the joint use of scientific and market knowledge and the performance of industrial inventors. In addition, similarly to the previous estimates, the sole use of market knowledge is also significantly related to inventors' quality. The coefficient for *mktonly* is indeed higher or very similar to that for *scimkt*. Therefore, it is arguable that the development of market channels is per se an influencing factor of the quality of the

[16] The total count and average of forward citations per technological class are calculated from the full patent sample in each region - thus not only on the sub-sample of respondents' patents.

[17] Hall et al. (2001) use the patent year as reference group for each patent, hence they weight the citation counts by the average citation count of patents granted in the same year.

[18] When a patent is classified into more than one technological class, its number of citations is weighted for the mean value of the average quality of each class.

[19] Note that the data in table 1.10 cannot be compared with those displayed in the histograms because the former are at inventor level whereas the diagrams display data at patent level.

inventors' patents, and thus, it is not possible to fully confirm that the joint use of market and scientific knowledge has systematically a higher impact on quality than the separate use of either scientific or market knowledge. Furthermore, the introduction of controls at firm level causes the variables of interest to lose significance, which may be due to firm-level factors that are unobserved. Overall, by using a better measure of inventors' quality it is possible to confirm the main findings, hence to conclude that inventors' performance is influenced by the use of external knowledge; however, it is not possible to conclude that the joint use of scientific and market knowledge has a stronger effect than the use of each of the sources separately.

1.7 Discussion and conclusion

This paper has investigated the role of scientific and market knowledge in the inventive process inside firms located in three European regions. We asked whether industrial patent inventors who exploit both types of knowledge at the same time display higher performance than those who use them separately. By applying an empirical framework only rarely employed at individual level, we estimate a model where the inventor's performance depends upon her knowledge sourcing strategies (using only scientific knowledge, using only market knowledge, using both of them) as well as a number of other individual, patent and firm level factors. The data comes from an original survey of private inventors who reside in Piedmont, Catalonia and the Midlands, combined with patent data from the European Patent Office.

Our findings show that there is a positive and significant relation between quantity of inventors' patents and the joint use of scientific and market knowledge. As far as quality of inventions is concerned, the results are slightly less neat because a relationship with the joint use of scientific and market knowledge does not always hold. Moreover, the sole use of knowledge from market sources is also significantly related to the quality of inventors in some of the estimations. In addition, mobile inventors benefit more than non-mobile ones from external knowledge, most likely because of their greater openness towards external-to-the-firm organisations. The robustness check carried out in the last section further shows that, when accounting for the uneven distribution of forward citations across different patent technological classes, the findings are consistent with the previous estimates. Finally, it is worth noticing that scientific knowledge seems to be never effective if used alone since the coefficient for the corresponding knowledge sourcing strategy never turns significant, and that some drivers of inventors' performance at firm-level may have remained unobserved, since the coefficients of interest lose significance once employer's factors are controlled for.

This paper has focused on three European regions, chosen as study cases because of their similar innovation performance, being all defined 'innovation followers' by the European Commission during the period of time that pertain the survey of inventors. The three regions display some differences in terms of patenting patterns, in that Piedmont shows higher figures than the other two regions. This emerges both from our study and from more comprehensive analyses, such as the European Commission Regional Innovation Scoreboard. From our estimates it appears that inventors residing in the Midlands produce less inventions for which they then apply for a patent at the EPO, than Piedmontese inventors, whereas no specific trends emerge with respect to Catalonia. However, no clear patterns emerge as fas as the quality of the inventions is concerned. Therefore, it seems arguable that, similarly to the overall results, the quantity of patents is clearly dependent upon knowledge sourcing strategies and, to a certain extent, to regional traits, whereas the driving factors of the quality of inventions still remain partly unobserved.

Before underlying the potential implications of this study, it is worth noticing that a number of limitations emerged. In first place, by administering the survey questionnaire to patent inventors only, non-patenting inventors have been automatically excluded from the sample, therefore nothing is known about the knowledge sourcing strategies of the latter group. This bias is partly overcome by taking into account both granted and not-yet granted patents. Moreover, the cross-sectional nature of the data does not allow to properly control for time-invariant factors. Finally, although forward citations are widely acknowledged as being among the best proxies for patent quality, it is also well-known that these have some limitations. In the attempt to improve it, we created a weighted count of forward citations.

Yet, the findings of this study offer some contributions to the literature. Firstly, the focus of this paper is on the individual who is primarily responsible for the inventive activity behind patents, this being justified by the fact that innovation is not simply the product of firms and organisations, but it also requires individual creativity. Whereas previous evidence has extensively focused on the role of organisational-level factors and/or intrinsic patent features in explaining the outcomes of innovative activities (see e.g. Hall et al., 2005; Harhoff et al., 1999; Pasquini et al., 2012; Suzuki, 2011), in this paper individual decisions are taken into account as fundamental drivers of individual outcomes.

Existing evidence suggests that inventors should rely on different sources of knowledge to increase the chances of patent commercialisations (Pasquini et al., 2012), though it seems that the opposite is true for the value of patented inventions (Schneider, 2009). This study adds that quantity as well as quality of inventors' patents benefit from the recombination of different sources of external knowledge. In addition, in order to analyse the role of inventors' knowledge sourcing strategies, the empirical analysis makes use of an original data source: the PICK-ME survey of industrial inventors in fact provides brand new insights about the demand of knowledge expressed by the actors directly involved in the innovative process within regions and also provides a number of information at individual level, including biographical information, that are not available from patent applications.

This study also offers some implications for innovation policies. In particular, the evidence of a complementarity relationship between different sources of knowledge for the inventive process supports the well-known argument that knowledge exchange across a wide range of organisations - both academic and non-academic - is beneficial to the innovation performance and the competitiveness of regions. This is particularly true with respect to universities, given that the latter often appears to be among the less important sources of external knowledge, notably if compared to firms (Giuri et al., 2007). In particular, since our study addresses individual innovativeness, it is arguable that knowledge sharing between firms' employees and universities or public research centres, as well as other market actors, require constant effort and investment in establishing relationships. Policies that creates incentives for information and idea sharing with external agents, as well as across firms' departments, could be beneficial to improve the overall organisational innovative process and, in turn, the innovation performance of regions.

1.8 Tables

		Npat			*Meanfcc*			*Maxfcc*		
	Obs.	**Mean**	**Min**	**Max**	**Mean**	**Min**	**Max**	**Mean**	**Min**	**Max**
CATALONIA	225	1.57	1	15	2.04	0	25	2.81	0	39
MIDLANDS	117	1.57	1	8	2.06	0	17	3.02	0	35
PIEMONTE	533	1.98	1	27	2.32	0	45.33	3.42	0	114
FULL SAMPLE	875	1.82	1	27	2.21	0	45.33	3.21	0	114

Table 1.1: Descriptive statistics of the dependent variables

Sources of knowledge	**Types of knowledge**
Suppliers of equipment/materials	
Clients and customers	MARKET KNOWLEDGE
Competitors	
Consultants and private R&D laboratories	
Universities	SCIENTIFIC KNOWLEDGE
Public research institutes	

Table 1.2: Sources of knowledge

Variable	**Obs.**	**Mean**	**1**	1a	1b	**2**	2a	2b	2c	2d
1 Scientific Know.	765	0.62	1							
1a University Know.	764	0.61	0.97	1						
1b Public research centres Know.	744	0.40	0.65	0.62	1					
2 Market Know.	783	0.91	0.20	0.21	0.23	1				
2a Clients Know.	761	0.71	0.16	0.15	0.22	0.52	1			
2b Competitors Know.	748	0.68	0.29	0.30	0.37	0.48	0.40	1		
2c Suppliers Know.	757	0.70	0.22	0.22	0.27	0.51	0.43	0.32	1	
2d Consultants Know.	745	0.54	0.46	0.46	0.48	0.36	0.31	0.33	0.31	1

Table 1.3: Descriptive statistics of the knowledge sources

			Means			Corr.		
Strategy	Freq.	Percent	*Npat*	*Meanfcc*	*Maxfcc*	*Npat*	*Meanfcc*	*Maxfcc*
1 scionly	23	3.06	1.57	1.92	2.30	-0.02	-0.02	-0.03
2 mktonly	235	31.25	1.70	2.42	3.31	-0.05	0.03	0.00
3 scimkt	444	59.04	1.98	2.30	3.51	0.09	0.01	0.04
4 noscimkt	50	6.65	1.34	1.56	1.92	-0.07	-0.05	-0.06

Table 1.4: Descriptive statistics of the independent variables

Variable	Description	Obs.	Mean	St.Dev.	Min	Max
Female	Dummy equal to 1 for female inventors	710	0.1014	0.3020	0	1
Age	Age of the inventor in 2006	710	44.4	10.212	22	79
Agesq	Age squared	710	2075.5	971.34	484	6241
HiSc	Secondary school degree	710	0.2225	0.4162	0	1
BSc	Bachelor degree	710	0.4014	0.4905	0	1
MSc	Master degree	710	0.1845	0.3881	0	1
PhD	Doctoral studies	710	0.1802	0.3846	0	1
Jobmobility	Dummy 1/0 for inventors who changed job at least once in 2000-06	710	0.6831	0.4656	0	1
R&Djob	Dummy 1/0 for inventors working in an R&D department	710	0.4436	0.4971	0	1
Retired	Dummy 1/0 for inventors who retired in 2000-06	710	0.0760	0.2652	0	1
Piedmont	Dummy 1/0 for inventors from Piedmont	710	0.5957	0.4911	0	1
Catalonia	Dummy 1/0 for inventors from Catalonia	710	0.2464	0.4312	0	1
Midlands	Dummy 1/0 for inventors from the Midlands	710	0.1577	0.3647	0	1
ost1	Electrical Engineering; Electronics	710	0.2802	0.4494	0	1
ost2	Instruments	710	0.1746	0.3794	0	1
ost3	Chemicals; Materials	710	0.1746	0.3799	0	1
ost4	Pharmaceuticals; Biotechnology	710	0.1183	0.3232	0	1
ost5	Industrial Processes	710	0.1915	0.3937	0	1
ost6	Mechanical Engineering; Machines; Transport	710	0.3704	0.4832	0	1
ost7	Civil Engineering; Consumer goods	710	0.1225	0.3281	0	1
Co-inventor	Dummy 1/0 for whether the inventor has ever co-invented a patent	710	0.7056	0.4561	0	1
Foreign pats	Share of inventors' patents owned by firms located abroad	710	0.1608	0.3637	0	1
Mne	Dummy 1/0 for whether the firm is a multinational company	710	0.5169	0.5000	0	1
Co-employment	Dummy 1/0 for inventors employed by the same firm	710	0.4985	0.5003	0	1

Table 1.5: Descriptive statistics of the control variables

	(1)	(2)	(3)	(4)
VARIABLES	*lNpat*	*lNpat*	*lNpat*	*lNpat*
scionly	-0.0287	-0.0397	-0.0274	-0.0234
	(0.125)	(0.147)	(0.133)	(0.210)
mktonly	0.0983	0.0583	0.0147	0.0943
	(0.0649)	(0.0657)	(0.0634)	(0.134)
scimkt	0.211***	0.181***	0.147**	0.198*
	(0.0620)	(0.0628)	(0.0600)	(0.118)
female	-0.004	-0.0027	-0.0348	0.110
	(0.0588)	(0.0590)	(0.0646)	(0.139)
age	0.0239*	0.0096	0.0104	0.0288
	(0.0136)	(0.0146)	(0.0139)	(0.0345)
agesq	-0.0002	-7.17e-05	-7.95e-05	-0.0003
	(0.0001)	(0.0001)	(0.0001)	(0.0003)
BSc	-0.0342	0.0340	0.0356	-0.0072
	(0.0603)	(0.0641)	(0.0568)	(0.127)
MSc	-0.107	-0.0459	-0.0342	-0.0319
	(0.0681)	(0.0728)	(0.0665)	(0.152)
PhD	-0.147**	-0.0380	-0.0296	0.188
	(0.0723)	(0.0766)	(0.0770)	(0.266)
jobmobility		0.0084	-0.0150	-0.0704
		(0.0461)	(0.0427)	(0.0937)
R&Djob		0.0451	0.0218	-0.0318
		(0.0482)	(0.0450)	(0.103)
retired		-0.0334	-0.0288	0.147
		(0.0990)	(0.0858)	(0.478)
coinventor			0.109**	0.258**
			(0.0463)	(0.104)
share_foreign_pat			0.0080	0.0010
			(0.0479)	(0.174)
mne				0.0217
				(0.424)
Catalonia		-0.1349***	-0.1947***	-0.0657
		0.0515	0.0476	0.2463
Midlands		0.1050*	0.0934	0.2453
		0.0630	0.0575	0.4357
Constant	-0.332	0.0835	-0.480	-1.040
	(0.323)	(0.358)	(0.357)	(1.106)
Year dummies	-	Yes	Yes	Yes
Patent techn. classes	-	-	Yes	Yes
Firm dummies	-	-	-	Yes
F-test (*scionly*,	F(3,731)=5.02	F(3,689)=4.10	F(3,680)=4.08	F(3,298)=1.27
mktonly, *scimkt*)	Pr>F=0.0019	Pr>F=0.0068	Pr>F=0.0069	Pr>F=0.2851
Observations	741	710	710	710
R-squared	0.027	0.111	0.278	0.699

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 1.6: OLS regression. Dependent variable: log of $Npat$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	*Meanfcc*	*Meanfcc*	*Meanfcc*	*Meanfcc*	*Maxfcc*	*Maxfcc*	*Maxfcc*	*Maxfcc*
scionly	0.335	0.614	0.708	1.137	0.386	0.811	1.087	1.283
	(0.784)	(0.875)	(0.914)	(2.515)	(0.878)	(1.011)	(1.099)	(3.142)
mktonly	0.754**	0.650*	0.495	0.536	1.279**	1.010**	0.675	0.746
	(0.380)	(0.358)	(0.364)	(1.003)	(0.509)	(0.486)	(0.505)	(1.749)
scimkt	0.678*	0.721**	0.608*	0.534	1.522***	1.492***	1.265**	1.295
	(0.360)	(0.351)	(0.365)	(0.946)	(0.534)	(0.534)	(0.567)	(1.488)
female	0.206	0.211	0.307	1.081	-0.0383	-0.0841	0.0182	1.362
	(0.485)	(0.495)	(0.482)	(1.160)	(0.677)	(0.669)	(0.647)	(1.631)
age	0.176**	0.0766	0.0597	0.207	0.245**	0.105	0.0692	0.413
	(0.0785)	(0.0714)	(0.0703)	(0.212)	(0.114)	(0.106)	(0.0974)	(0.352)
agesq	-0.002**	-0.001	-0.0008	-0.0026	-0.0026**	-0.0014	-0.001	-0.0048
	(0.0008)	(0.0007)	(0.0007)	(0.0022)	(0.0012)	(0.0011)	(0.0010)	(0.0037)
BSc	-0.380	-0.293	-0.324	-0.557	-0.373	-0.205	-0.203	-0.309
	(0.351)	(0.346)	(0.347)	(0.812)	(0.509)	(0.484)	(0.479)	(1.321)
MSc	-0.389	-0.471	-0.418	-0.686	-0.176	-0.209	-0.0822	0.402
	(0.515)	(0.510)	(0.537)	(1.423)	(0.968)	(0.954)	(1.035)	(3.081)
PhD	-0.321	-0.249	-0.183	-1.460	-0.387	-0.0579	0.240	-0.0196
	(0.446)	(0.454)	(0.539)	(1.413)	(0.670)	(0.678)	(0.892)	(2.744)
jobmobility		-0.0525	-0.0759	0.233		-0.184	-0.285	-0.122
		(0.299)	(0.309)	(0.592)		(0.538)	(0.572)	(1.022)
R&Djob		0.518*	0.515*	0.252		0.893**	0.838*	0.244
		(0.289)	(0.294)	(0.633)		(0.425)	(0.445)	(0.858)
retired		-0.117	-0.224	2.214		-0.0390	-0.161	1.955

		(0.464)	(0.469)	(2.710)		(0.811)	(0.824)	(5.030)
coinventor			0.546**	0.995			1.152***	2.600*
			(0.259)	(0.791)			(0.397)	(1.343)
share_foreign_pat			0.184	-0.612			-0.0292	-0.821
			(0.329)	(0.996)			(0.421)	(1.480)
mne				-3.513				-4.486
				(3.058)				(4.851)
Catalonia		0.3033	0.3355	0.1722		0.0773	0.0279	0.7536
		0.3220	0.3640	1.4710		0.4765	0.5383	2.8692
Midlands		0.2018	0.2206	-2.1168		0.1587	0.2466	0.1023
		0.3810	0.4105	3.4474		0.5422	0.5883	5.1763
Constant	-1.852	2.617	2.335	-0.869	-3.173	3.367	1.801	-3.947
	(1.833)	(1.696)	(1.798)	(7.041)	(2.648)	(2.592)	(2.618)	(10.91)
Year dummies	-	Yes	Yes	Yes	-	Yes	Yes	Yes
Patent techn. classes	-	-	Yes	Yes	-	-	Yes	Yes
Firm dummies	-	-	-	Yes	-	-	-	Yes
F-test (*scionly*,	F(3,731)=1.57	F(3,689)=1.54	F(3,680)=0.97	F(3,298)=0.14	F(3,731)=3.37	F(3,689)=2.75	F(3,680)=1.68	F(3,298)=0.27
mktonly, *scimkt*)	Pr>F=0.1962	Pr>F=0.2030	Pr>F=0.4048	Pr>F=0.9384	Pr>F=0.0182	Pr>F=0.0420	Pr>F=0.1699	Pr>F=0.8491
Observations	741	710	710	710	741	710	710	710
R-squared	0.009	0.137	0.154	0.564	0.007	0.116	0.150	0.444

Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table 1.7: OLS regression. Dependent variables: $Meanfcc$ (col. (1)-(4)), $Maxfcc$ (col. (5)-(8))

	Mobile inventors		Non-mobile inventors	
VARIABLES	*lNpat*	*lNpat*	*lNpat*	*lNpat*
scionly	0.0428	-0.0187	-0.132	-0.188
	(0.181)	(0.177)	(0.0888)	(0.125)
mktonly	0.0675	-0.0161	0.154	0.0747
	(0.0919)	(0.0887)	(0.0951)	(0.0937)
scimkt	0.202**	0.146*	0.257***	0.168*
	(0.0914)	(0.0865)	(0.0912)	(0.0876)
Constant	-0.252	-0.300	-0.274	-0.483
	(0.445)	(0.509)	(0.522)	(0.519)
Region dummies	-	Yes	-	Yes
Year dummies	-	Yes	-	Yes
Patent techn. classes	-	Yes	-	Yes
Firm dummies	-	-	-	-
F-test (*scionly*,	F(3,475)=2.58	F(3,456)=3.45	F(3,216)=11.62	F(3,196)=3.41
mktonly, *scimkt*)	Pr>F=0.0532	Pr>F=0.0165	Pr>F=0.0000	Pr>F=0.0185
Observations	485	485	225	225
R-squared	0.038	0.280	0.044	0.351

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 1.8: OLS regression. Dependent variable: log of $Npat$, breakdown by inventors' mobility

	Mobile inventors		Non-mobile inventors		Mobile inventors		Non-mobile inventors	
VARIABLES	*Meanfcc*	*Meanfcc*	*Meanfcc*	*Meanfcc*	*Maxfcc*	*Maxfcc*	*Maxfcc*	*Maxfcc*
scionly	0.0159	-0.0125	2.700	3.523	0.365	0.283	2.111	3.326
	(0.607)	(0.680)	(2.821)	(3.147)	(0.897)	(0.962)	(2.986)	(3.733)
mktonly	1.077**	0.547	0.826	0.764	1.606**	0.757	1.292	1.096
	(0.485)	(0.466)	(0.629)	(0.614)	(0.660)	(0.629)	(0.871)	(1.056)
scimkt	1.236***	0.844*	0.499	0.653	2.055***	1.464**	1.514	1.697
	(0.461)	(0.487)	(0.603)	(0.637)	(0.668)	(0.679)	(1.121)	(1.219)
Constant	-2.554	2.287	-0.727	0.942	-3.780	2.059	-3.790	-0.142
	(2.415)	(2.589)	(3.433)	(3.113)	(3.247)	(3.585)	(6.176)	(5.271)
Region dummies	-	Yes	-	Yes	-	Yes	-	Yes
Year dummies	-	Yes	-	Yes	-	Yes	-	Yes
Patent techn. classes	-	Yes	-	Yes	-	Yes	-	Yes
Firm dummies	-	-	-	-	-	-	-	-
F-test (*scionly*,	F(3,475)=4.02	F(3,456)=1.49	F(3,216)=0.79	F(3,196)=0.85	F(3,475)=4.32	F(3,456)=2.01	F(3,216)=1.12	F(3,196)=0.94
mktonly, *scimkt*)	Pr>F=0.0077	Pr>F=0.2163	Pr>F=0.5018	Pr>F=0.4659	Pr>F=0.0051	Pr>F=0.1113	Pr>F=0.3416	Pr>F=0.4210
Observations	485	485	225	225	485	485	225	225
R-squared	0.028	0.188	0.022	0.180	0.031	0.229	0.016	0.165

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 1.9: OLS regression. Dependent variables: $Meanfcc$ and $Maxfcc$, breakdown by inventors' mobility

	CATALONIA	MIDLANDS	PIEDMONT
electrical eng	1.25	1.15	0.95
instruments	1.09	0.51	1.27
chemicals	0.88	0.41	0.83
pharmaceuticals	0.88	0.23	0.97
industrial eng	0.95	1.20	1.10
mechanical eng	1.22	0.74	1.31
civil eng	1.20	0.89	0.73

Table 1.10: Mean values of *Meanfcc_weighted*, breakdown by technological class and region

VARIABLES	**(1)** *Meanfcc_w*	**(2)** *Meanfcc_w*	**(3)** *Meanfcc_w*	**(4)** *Meanfcc_w*	**(5)** *Meanfcc_w*
scionly	0.290	0.284	0.423	0.476	0.660
	(0.418)	(0.434)	(0.482)	(0.498)	(1.377)
mktonly	0.410**	0.357**	0.319*	0.257	0.323
	(0.176)	(0.177)	(0.167)	(0.171)	(0.465)
scimkt	0.359**	0.335**	0.340**	0.306*	0.273
	(0.165)	(0.168)	(0.161)	(0.167)	(0.426)
Constant	0.714***	-0.709	1.059	0.808	-1.914
	(0.138)	(0.893)	(0.808)	(0.860)	(3.680)
Personal charact.	-	Yes	Yes	Yes	Yes
Reg. & year dummies	-	-	Yes	Yes	Yes
Pat. techn. classes	-	-	-	Yes	Yes
Firm dummies	-	-	-	-	Yes
F-test (*scionly*,	F(3,741)=2.06	F(3,728)=1.63	F(3,686)=1.67	F(3,677)=1.20	F(3,297)=0.20
mktonly, scimkt)	Pr>F=0.1045	Pr>F=0.1805	Pr>F=0.1726	Pr>F=0.3072	Pr>F=0.8984
Observations	745	738	707	707	707
R-squared	0.003	0.010	0.140	0.157	0.560

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 1.11: OLS regression. Dependent variable: *Meanfcc_weighted*

1.9 Figures

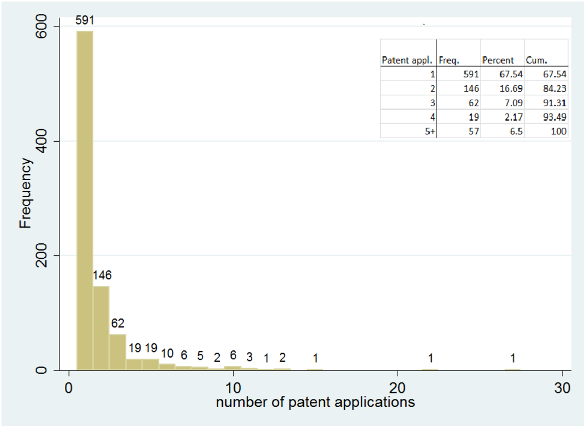

Figure 1.1: Distribution of patent applications per inventors

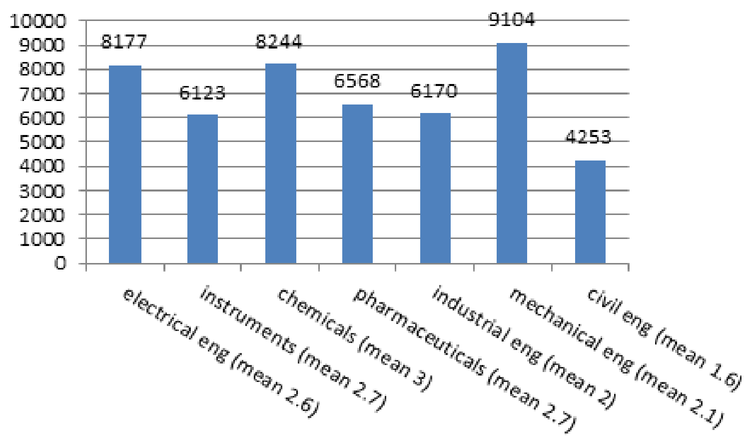

Figure 1.2: Forward citations of all patents by technological class

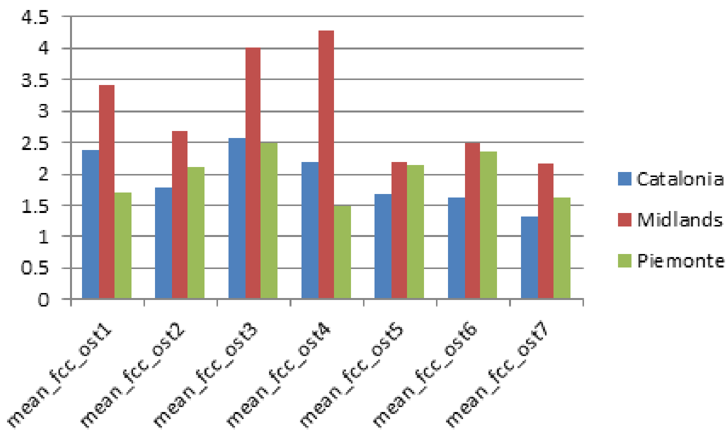

Figure 1.3: Mean forward citations by technological class and region

1.10 Appendix

Variable	Obs.	Mean	St.Dev.	Min	Max
Female	881	0.1044	0.3059	0	1
Age	870	44.72	10.390	22	79
Agesq	870	2107.67	990.83	484	6241
HiSc	881	0.2315	0.4220	0	1
BSc	881	0.3904	0.4881	0	1
MSc	881	0.1702	0.3760	0	1
PhD	881	0.1634	0.3699	0	1
Jobmobility	807	0.6741	0.4690	0	1
R&D	832	0.4290	0.4952	0	1
Retired	831	0.0746	0.2629	0	1
Piedmont	881	0.6118	0.4876	0	1
Catalonia	881	0.2554	0.4363	0	1
Midlands	881	0.1328	0.3395	0	1
ost1	875	0.272	0.4452	0	1
ost2	875	0.1782	0.383	0	1
ost3	875	0.1748	0.3800	0	1
ost4	875	0.1154	0.3197	0	1
ost5	875	0.192	0.3941	0	1
ost6	875	0.3782	0.4852	0	1
ost7	875	0.1291	0.3355	0	1
Co-inventor	875	0.7085	0.4546	0	1
Foreign pats	875	0.1652	0.3677	0	1
Mne	881	0.4892	0.5001	0	1
Co-employment	881	0.4687	0.4993	0	1

Table 1.12: Descriptive statistics of the control variables, full sample

Variable	**Description**	**Construction**	**Source**
lNpat	Log of patent count	Log of number of applied/granted patents per inventor	Patent data
Meanfcc	Mean forward citation count	Mean number of forward citations received by inventors' patents	Patent data
Maxfcc	Highest forward citations	Highest number of forward citations received by inventors	Patent data
Meanfcc weighted	Weighted forward citations	Forward citations weighted for mean citation count per technological class	Patent data
SCIKnow	Scientific knowledge	Dummy equal 1 if respondents used at least one source of scientific knowledge	Survey
MKTKnow	Market knowledge	Dummy equal 1 if respondents used at least one source of market knowledge	Survey
scionly	Only scientific knowledge	Dummy equal 1 if respondents used only scientific knowledge	Survey
mktonly	Only market knowledge	Dummy equal 1 if respondents used only market knowledge	Survey
scimkt	Both scientific and market knowledge	Dummy equal 1 if respondents used both scientific and market knowledge	Survey
noscimkt	Neither scientific nor market knowledge	Dummy equal 1 if respondents used neither scientific nor market knowledge	Survey
Female	Gender of inventors	Dummy equal 1 for female inventors	Survey
Age	Age of inventors	Age of inventors in 2006	Survey
Agesq	Age squared	Square of Age	Survey
HiSc	Secondary school degree	Dummy equal 1 if respondents obtained a secondary school degree	Survey
BSc	Bachelor degree	Dummy equal 1 if respondents obtained a bachelor degree	Survey
MSc	Master degree	Dummy equal 1 if respondents obtained a master degree	Survey
PhD	Doctoral studies	Dummy equal 1 if respondents obtained a PhD degree	Survey
Jobmobility	Inventors' job mobility	Dummy equal 1 if respondents changed job at least once in 2000-06	Survey
R&Djob	Inventors R&D job	Dummy equal 1 if respondents work on R&D-related task or in an R&D division/department inside the company	Survey
Retired	Inventors' retirement status	Dummy equal 1 if respondents retired in 2000-06	Survey

Piedmont	Inventors from Piedmont	Dummy equal 1 if respondents are Piedmont residents	Survey
Catalonia	Inventors from Catalonia	Dummy equal 1 if respondents are Catalonia residents	Survey
Midlands	Inventors from the Midlands	Dummy equal 1 if respondents are Midlands residents	Survey
ost1	Electrical Engineering; Electronics	Dummy equal 1 if respondents' patents are classified in Electrical Eng. and Electronics technological class	Patent data
ost2	Instruments	Dummy equal 1 if respondents' patents are classified in Instruments technological class	Patent data
ost3	Chemicals; Materials	Dummy equal 1 if respondents' patents are classified in Chemicals and Materials technological class	Patent data
ost4	Pharmaceuticals; Biotechnology	Dummy equal 1 if respondents' patents are classified in Pharmaceuticals and Biotechnology technological class	Patent data
ost5	Industrial Processes	Dummy equal 1 if respondents' patents are classified in Industrial processes technological class	Patent data
ost6	Mechanical Eng.; Machines; Transport	Dummy equal 1 if respondents' patents are classified in Mechanical Eng., Machines, Transport technological class	Patent data
ost7	Civil Eng.; Consumer goods	Dummy equal 1 if respondents' patents are classified in Engineering and Consumer goods technological class	Patent data
Co-inventor	Co-inventorship on a patent	Dummy equal 1 if respondents have ever co-invented	Patent data
Foreign pats	Share of foreign patents	Share of inventors' patents owned by firms located abroad	Patent data
Mne	Multinational enterprise	Dummy equal 1 if respondents' employer has facilities and other assets in at least one country other than its home country	Web search
Co-empl.	Inventors employed by the same firm	Dummy equal 1 if respondents are employed by the same firm	Survey
Year dum.	Year of first patent in 2000-2006	Dummies for year of first patent (priority date) in 2000-2006	Patent data
Firm dum.	Inventors' employers	Dummies for respondents' employers in 2006	Survey

Table 1.13: Description of the variables used in the regression analysis

VARIABLES	(1) *Npat*	(2) *Npat*	(3) *Npat*	(4) *Npat*
scionly	0.214 (0.237)	0.241 (0.238)	0.186 (0.228)	0.207 (0.312)
mktonly	0.214 (0.150)	0.130 (0.150)	0.0578 (0.144)	0.138 (0.210)
scimkt	0.406*** (0.145)	0.347** (0.145)	0.274** (0.139)	0.316 (0.204)
female	-0.102 (0.111)	-0.104 (0.114)	-0.155 (0.112)	0.0431 (0.155)
age2006	0.0407* (0.0247)	0.0189 (0.0252)	0.0259 (0.0246)	0.0530 (0.0421)
age06_2	-0.000376 (0.000258)	-0.000131 (0.000266)	-0.000213 (0.000258)	-0.000595 (0.000459)
BSc	-0.0317 (0.0820)	0.0470 (0.0855)	0.0350 (0.0830)	-0.0815 (0.127)
MSc	-0.175* (0.105)	-0.0826 (0.109)	-0.0901 (0.105)	-0.0582 (0.156)
PhD	-0.162 (0.106)	-0.0282 (0.124)	-0.0467 (0.128)	0.314 (0.219)
job_m		0.0193 (0.0726)	0.00555 (0.0692)	-0.116 (0.1000)
r_d		0.0580 (0.0685)	0.00847 (0.0657)	-0.0716 (0.107)
retired		-0.134 (0.152)	-0.108 (0.144)	0.309 (1.413)
coinventor			0.123* (0.0727)	0.374** (0.150)
share_foreign_pat			-0.0420 (0.0950)	-0.0149 (0.217)
mne				0.0817 (1.316)
Constant	-0.664 (0.589)	0.126 (0.608)	-0.671 (0.607)	-1.891 (1.451)
Year dummies	-	Yes	Yes	Yes
Patent techn. classes	-	-	Yes	Yes
Firm dummies	-	-	-	Yes
Likelihood-ratio test of $alpha = 0$	$\bar{\chi}^2 = 82.78$ $Pr \geq \bar{\chi}^2 = 0$	$\bar{\chi}^2 = 50.44$ $Pr \geq \bar{\chi}^2 = 0$	$\bar{\chi}^2 = 13.37$ $Pr \geq \bar{\chi}^2 = 0$	$\bar{\chi}^2 = 0$ $Pr \geq \bar{\chi}^2 = 1$
Observations	741	710	710	710
Pseudo R2	0.0101	0.0397	0.0914	0.2345

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 1.14: Negative binomial regression. Dependent variable: $Npat$

Chapter 2

University-Industry collaboration and firms' R&D effort

2.1 Introduction

Nowadays firms are embedded in networks of strategic alliances throughout which they gain competitive advantage from continuous scientific and technical interactions (Owen-Smith and Powell, 2004). In particular, firms need to find and use new sources of knowledge in order to innovate and grow and universities are often the main repository of such knowledge. The exchange of knowledge between academia and industry is therefore an essential mechanism to bring science to the market and foster innovation and economic growth (OECD, 1998, 2002a).

University-industry knowledge transfer is a broad concept identifying a wide set of interactions between firms and universities. In particular, university-industry research collaboration is a specific channel of inter-organisational knowledge flows and potential spillovers from (and to) academic research aimed at carrying out specific R&D projects, particularly involving pre-competitive and basic research (OECD, 1998, 2002a; D'Este and Fontana, 2007; D'Este and Iammarino, 2010; D'Este et al., 2013). Cooperative research partnerships are among the most typical forms of U-I research collaborations, followed by contract research, research consortia, consulting and founding of co-operative research centres (OECD, 1998; Fontana et al., 2006). The relevance of this typology of interaction channel is shown by the fact that it represents one of the most frequent policy instruments put in place by local and national policy-makers to foster pre-competitive research and firms' innovation activities (OECD, 1998, 2002a; Fisher et al., 2009; D'Este and Iammarino, 2010).

U-I cooperative R&D projects can be seen as a voluntary (or intended) and reciprocal information mechanism that enhances learning processes and performance of the partnering organisations (Feldman and Kelley, 2006). For this reason U-I R&D cooperation is considered a valid proxy for explaining knowledge generation associated with knowledge spillovers (see e.g. Cincera et al., 2003). However, the innovation literature has been, so far, only partly conclusive with regards to the impact that these activities have on firms' performance. Following the perspective that R&D cooperation can be seen as a vehicle for voluntary knowledge transfer, the present study intends to fill this gap by assessing the effect of publicly funded U-I R&D projects on firms' R&D effort. By relying on a novel dataset of U-I partnerships combined with firm-level data and by employing propensity score matching to select a control group of untreated firms, we investigate the impact of U-I R&D projects on firms' R&D expenditure per employee and share of R&D employment.

This paper contributes to the literature on university-industry knowledge transfer by bringing new evidence on the impact that the publicly funded voluntary exchange of knowledge between university and firms has on firms' internal effort on R&D. We do so by analysing the case of U-I partnerships funded by the UK Engineering and Physical Sciences Research Council, on which only limited empirical evidence exists as far their impact on firms is concerned. Our data on U-I partnerships provides information on firms involved in a full range of projects funded during a 10 years time span; hence, by matching this with firm-level data, we create a new and original dataset that allows us to carry out an evaluation study of a specific U-I R&D programme. Moreover, the employment of propensity score matching helps us to tackle the issue of selection bias typically arising in quasi-experimental settings and provides a useful tool to work out a sensible control group of non-participating firms to be compared to participating firms.

The remainder of the paper is organised as follows: in section 2.2 we provide a review of the literature, which, together with an overview of the programme under study, leads to the hypotheses of the paper; in section 2.3 we describe our data and illustrate the construction of the dataset; section 2.4 is dedicated to the illustration of the methodology; in section 2.5 we describe the outcome variables and present the empirical results; finally, we conclude the paper by summing up and discussing our findings in section 2.6.

2.2 Literature and hypotheses development

2.2.1 U-I knowledge interaction

External knowledge acquisition is necessary for innovation activities carried out by firms, especially in the current context of market globalisation and rapid technological change. Both the early literature on technological change (see e.g. Allen and Cohen, 1969; Allen, 1977) and the more recent studies on the knowledge sourcing strategies of firms (see e.g. Arora and Gambardella, 1990, 1994; Cassiman and Veugelers, 2006, 2007; Frenz and Ietto-Gillies, 2009) assert that firms cannot rely only on their internal resources and have to tap into knowledge outside their boundaries in order to successfully produce innovation. In particular, the seminal works of e.g. Griliches (1987), Jaffe (1989) and Adams (1990), have uncovered the role of knowledge from universities for innovation activities of firms and for economic development more in general. Since then, the literature on university-industry knowledge interaction has grown substantially (see e.g. Mansfield, 1995; Mansfield and Lee, 1996; Cohen et al., 2002), showing that firms exploit university knowledge in order to produce innovations and stay competitive on the market.

U-I knowledge transfer is a broad concept identifying a wide set of interactions between firms and universities that are aimed at the exchange of knowledge related to research, science and technology. In particular, U-I research collaboration include research partnerships, contract research, research consortia, consulting and founding of co-operative research centres. In this paper we study publicly funded U-I cooperative R&D partnerships, which are aimed at carrying out specific R&D projects, particularly involving pre-competitive and basic research. These typically involve formal agreements that entail cash and in-kind contributions by both sides, so that university and firms share not only their knowledge and competencies but also their R&D facilities and personnel (D'Este et al., 2013).

The Systems of Innovation (SI) literature, particularly the national innovation systems (NSI) concept, rooted in the seminal work of Freeman (1987), recognises that proper government policies are needed to ensure timely access by innovators to stocks of knowledge held in firms and institutions, thus allowing the development of those technical capabilities that lie at the core of countries' competitiveness (David and Foray, 1995; Grupp, 1995). Governments have the responsibility to set rules and create institutional frameworks that provide the right incentives for interactions (Bozeman, 2000). As a matter of fact, research collaborations between universities and businesses are among the most frequent policy instruments put in place by local and national policy-makers to foster pre-competitive research and firms' innovation activities (OECD, 1998, 2002a; Fisher et al., 2009; D'Este and Iammarino, 2010).

2.2.2 U-I research collaboration and firms' performance

The relationship between U-I research collaboration and firm-level performance has been addressed by different strands of the empirical literature. It is mostly within the literature on R&D cooperation, knowledge spillovers and productivity - in which U-I collaboration is considered a typology of R&D cooperation - that this issue is addressed. In addition, within the innovation literature that specifically looks at technology and knowledge transfer, the attention has recently extended to the effects of U-I activities.

The literature on R&D cooperation, knowledge spillovers and productivity investigates firms' R&D interactions with external organisations (including universities) and predicts that firms engage into cooperative R&D because this enables them to internalise knowledge spillovers and eliminate the disincentive effect of spillovers on R&D (Steurs, 1995; De Bondt, 1997; Cassiman and Veugelers, 2002; Belderbos et al., 2004; Schmidt, 2005; Lopéz, 2008). Firms engage into joint R&D also because it allows the acquisition and utilization of external resources for their own purposes directly and systematically (Hagedoorn, 1993; Scott, 1996; Hite and Hesterly, 2001; Caloghirou et al., 2003) and sharing costs and risks among partners (Sakakibara, 1997; Beath et al., 1998). Hence, the benefits associated to R&D cooperation can be attributed to: reducing uncertainty; joint financing of R&D; realizing cost-savings; realizing economies of scale and scope (Camagni, 1993; Robertson and Langlois, 1995; Becker and Dietz, 2004). Accordingly, scholars have been searching for the impact of R&D cooperation at the level of both firms' innovation activities (input and output) and firm productivity.

A positive impact of engaging in R&D cooperation has been tracked down on the innovation performance (innovation output) of firms, such as sales of innovative products (see e.g. Klomp and Van Leeuwen, 2001; Lööf and Heshmati, 2002; Criscuolo and Haskel, 2003; Faems et al., 2005), patenting (Vanhaverbeke et al., 2002), and sales growth (Cincera et al., 2003). Some of these studies also examine the effect of different cooperation typologies, but have produced ambiguous results. Faems et al. (2005) used cross-section data from the Belgian CIS survey in 1992 and found a positive association between university cooperation and the share in firm sales of innovative products new to the market, while an aggregate measure of other cooperation typologies was positively associated with the share in firm sales of innovative products new to the firm (but not new to the market).

Monjon and Waelbroeck (2003) regressed innovative sales levels of firms in a French CIS survey on a range of collaboration and incoming knowledge spillover variables and found a mixture of negative and positive effects of R&D cooperation and spillovers. Belderbos et al. (2004), using the Dutch CIS, distinguish between four typologies of cooperation and find that R&D collaboration with competitors and universities has a significant and positive impact on the growth of innovative sales, but has no significant impact on labour productivity.

Furthermore, a number of studies look at R&D cooperation supported by public funding, particularly EU funding: for instance, Benfratello and Sembenelli (2002) show that firms' participation to the EUREKA research joint ventures programme experienced an improvement in their economic performance, while firms participating to the third and fourth Framework Program (FP) showed no clear impact; Barajas et al. (2011), using data on

Spanish participants to the EU FP research joint ventures, confirm that R&D cooperation has a positive effect on the technological capacity of firms, which is found to be positively related to productivity.

Some of these studies are based on one or more waves of innovation surveys, hence relying on self-reported measures and, often, cross-sectional data, which could explain the reason for such a high variation in the results. In addition, there may be unobservable firm characteristics that affect both the innovation or productivity outcome and, at the same time, the decision to engage into cooperative research, that are only rarely accounted for.

The innovation literature on technology and knowledge transfer has extensively looked at the determinants, characteristics and barriers of U-I knowledge transfer activities. More recently, the focus has moved on the effects of these activities. Similarly to the literature on firms' R&D cooperation, empirical studies in this strand of literature distinguish between the impact of knowledge transfer on firms' innovative activities and the impact on overall firms' economic performance. Most of the studies that exploit direct measures of knowledge interactions, such as U-I R&D cooperation, or the use of university as an external knowledge source, find positive effects on firms' innovative activities, including R&D intensity (innovation input), the propensity to register new patents as well as the introduction and sales of new products (innovation output) (see e.g. Becker, 2003; Fritsch and Franke, 2004; Arvanitis et al., 2008; Lööf and Broström, 2008).

On the contrary, studies that investigate the impact of university knowledge on the overall economic performance of firms (i.e. labour productivity, total factor productivity) show contradicting evidence: Medda et al. (2006) found no significant effect of collaborative research undertaken by Italian manufacturing firms and universities on the growth of total factor productivity, whereas other studies found a positive effect on different measures of labour productivity, sales productivity or sales growth (see e.g. Belderbos et al., 2004; Branstetter and Ogura, 2005). The observed differences among the findings of these studies can be partly traced back to the nature of the investigation (cross-section versus longitudinal), but also to differences with respect to the industrial sectors covered by these studies.

To sum up, this overview of the literature on the impact of U-I collaboration on firms shows that, even though this subject has attracted attention from different strands of the literature, evidence is still quite mixed, hence calling for further research. To some extent, there seems to be convergence towards a positive impact on firms, but this is far from being unquestionable. In addition, the motivations for evaluating the impact on firms' performance or rather on innovative activities (or both) - and, in the latter case, whether it is more appropriate to look at innovation input or output measures - are not always well grounded into the policy discourse. In the next section we present the UK policy context that is concerned with U-I linkages and the specific policy under study. This will help us to build the empirical hypotheses.

2.2.3 UK policy for U-I interaction: the case of EPSRC research collaborations

From the 1980s onwards it is possible to distinguish three phases of UK government policy towards U-I knowledge transfer (Lawton Smith and Bagchi-Sen, 2006). Running from the 1980s until the 1990s, the first phase was characterised by the government's intention to push universities towards the exploitation of the intellectual property rights of their researchers. The 1998 White Paper of the Department of Trade and Industry (DTI, 1988) particularly signalled this intention, together with the ending in 1985 of the British Technology Group's right of refusal of inventions arising from universities' public funded research. The turning point between the first and second phase can be traced back to the release of the 1993 White Paper Realising our Potential (DTI, 1993), which was followed by a series of initiatives designed with the objective to better exploit the UK's strengths in science and technology through partnerships between the science base, UK industry and government. The following White Paper on Competitiveness (DTI, 1995) saw a shift from large R&D programmes to smaller and targeted schemes aimed at improving U-I interactions and best practice.

The third phase, initiated in 1997 by the new political agendas of the newly elected Labour government, was about restoring R&D funding that had previously decreased, and constant commitment to the valorisation of research. Moreover, a 'territorialisation' agenda was introduced, assigning to universities and regional development agencies the task of promoting innovation in a given geographical area (Lawton Smith and Bagchi-Sen, 2006).[1] During this phase, the development and empowerment of knowledge-based industry became a priority (Lawton Smith, 2003) and the role of universities for the UK economy was further emphasised by the 2003 Lambert Review of University-Business Interaction, particularly at the local level (Lambert, 2003). The latter recommended the formation of both formal and informal networks between the academic community and businesses, along with a greater role for universities and local institutions in facilitating interactions at the regional level.

This paper considers U-I collaborative partnerships that have been funded between 1998 and 2007, hence during the third phase of UK government policy on U-I linkages, by the Engineering and Physical Sciences Research Council (EPSRC). The EPSRC is one of the seven UK research councils responsible for administering public funding for research in the UK. It distributes more than 20% of the total UK science budget, being the largest council in terms of the volume of research funded (D'Este et al., 2013). The EPSRC provides funding to national research through a wide range of grant schemes. In this paper we consider U-I partnerships supported through standard grants and through the LINK grant scheme.[2]

These partnerships are aimed at contributing to joint upstream research for the creation of new knowledge and, thus, they are far from industrial applications. They exclude contract research paid by the company to have a specific, well-defined outcome. Intended benefits for partnering companies include the provision of financial support for the project, helping companies to develop closer relationships with the science base and creating the opportunity for recruiting appropriately trained staff at the end of the

[1] Regional development agencies were established in England between 1998 and 2000, and abolished in 2012.

[2] Collaboration from industry is encouraged but not mandatory under the standard grant schemes, thus we only considers projects where firms are involved. The LINK scheme instead specifically provided funding for collaborative research between at least one science-based organisation and one business partner. This was an initiative of the Department for Business Innovation and Skills administered through the UK Research Councils. Around 70% of the partnerships supported between 1992 and 2007 by the EPSRC were funded under the Standard Research Grant Scheme (now called Research Base Funding), followed by the LINK grant scheme (10%).

project. In each project, UK Higher Education Institutions take the role of project coordinator (i.e. Principal Investigator) whereas collaborators from industry, commerce and other organisations work as partners.

As far as the selection process is concerned, the EPSRC receives applications proposals from the principal investigators and expects that the participants in a collaborative projects develop an agreement that clarifies the contribution of each partners; however, it does not get involved in the negotiation of the agreement, nor in the selection of partners from industry.

U-I collaborative partnerships in engineering and physical sciences funded by the EPSRC have been the focus of several empirical studies and reports (see e.g. D'Este and Fontana, 2007; D'Este and Patel, 2007; Ambos et al., 2008; Bruneel et al., 2009, 2010; D'Este and Iammarino, 2010; Bishop et al., 2011; Crespi et al., 2011; D'Este et al., 2012, 2013), which uncovered a number of relevant aspects related to the determinants, typologies and barriers of collaborations. However, these studies offer little evidence on the effect of U-I interaction, especially on firms.

One exception is represented by Bruneel et al. (2009), whose report summarizes the results of two extensive surveys carried out in 2004 and 2008, designed to shed new lights on industry and university researchers' attitudes to collaborate. The surveys involved university and industry partners that participated to EPSRC collaborative projects after 2000. The report shows that the most important benefit of working with universities for firms is to create a long-term connection with the latter, followed by the opportunity to identify and recruit employees. The main benefits are hence attributable to developing knowledge and methods and getting access to highly skilled problem solvers (Bruneel et al., 2009). On the contrary, short-term benefits, such as cost reduction, turned out to be only marginally relevant for the respondents. Therefore, although not yet tested empirically, it emerges that UK firms collaborating with universities under the umbrella of the EPSRC look at universities as a source of ideas and talented people rather than a low cost pool of research services.

2.2.4 Hypotheses

The research question addressed in this paper is *'What is the impact of publicly funded U-I collaboration on firms' R&D activities in the UK?'*. The review of the literature presented in the previous section shows that scholars have searched for the impact of U-I collaboration both on firms' innovative and R&D activities and firms' overall productivity. In the first case, both R&D input (e.g. R&D expenditure) and output (e.g. sales of new products) have been used as outcome measures, although the former is less commonly employed than the latter. Results are quite mixed, although there seems to be agreement on a positive relation between U-I collaboration and firms' innovative activities.

Turning on the specificities of the EPSRC projects, we highlighted that their aim is to contribute to pre-competitive and upstream research and, in practice, they support companies financially, help them to establish a close relationship with universities and to create the conditions and opportunities for recruiting highly trained personnel. These aspects, which are all linked to R&D and innovation inputs, are confirmed by the findings in Bruneel et al. (2009), who shows that firms declared to find more beneficial the contribution of university to knowledge creation and recruitment of personnel rather than to the production of short-term outputs, such as new products. As a consequence, we argue that the impact of the EPSRC U-I research projects, because of their pre-competitive nature, should be searched on firms' R&D inputs.

Following inter alia Busom (2000), we focus on R&D intramural expenditure and R&D personnel. We argue that U-I collaboration entails higher firms' involvement in research activities, both in terms of knowledge production and financial engagement. In fact, firms contribute to EPSRC partnerships via cash and in-kind support, the latter including staff time, access to equipment, provision of data, software or materials.

In the first place, we expect the impact of U-I collaboration to be captured by differences in R&D equipments and/or costs, mirrored by R&D expenditure (Busom, 2000). R&D expenditure is one of the firm-specific determinants that influence the innovative behaviour of firms and it is commonly used as a measure of R&D input (Becker and Dietz, 2004).

Therefore, we put forward the following hypothesis:

Hp 1: U-I partnerships have a positive impact on the R&D expenditure per employee of participating firms.

Secondly, we argue that, through the network of relationships arising from the partnerships, U-I projects provide both the opportunity of hiring new R&D personnel at the end of the project and the chance of learning for existing staff. As stated in the OECD Frascati Manual (OECD, 2002b), data on the utilisation of scientific and technical personnel provide concrete measurement of resources devoted to R&D. Moreover, R&D personnel may mirror the human capital component of R&D that is usually more permanent (Busom, 2000). We expect that the share of employees working on R&D related tasks inside the firms increases after participation, hence we put forward our second hypothesis:

Hp 2: U-I partnerships have a positive impact on the share of R&D employment of participating firms.

2.3 Data

The empirics of the paper relies on a unique dataset, resulting from the combination of a dataset of EPSRC U-I partnerships funded between 1998 and 2007, with firm-level data gathered from two databases provided by the UK Office for National Statistics (ONS). The advantage of our dataset of U-I partnerships over other similar sources of data is that it provides information on actual interactions between firms and universities. Moreover, data are collected by the funding agency, thus ruling out any bias due to self-reported information, as it is the case for survey-based data. Hence, we believe that these data may represent a reliable proxy for knowledge transfer activities between businesses and academia.

The EPSRC dataset includes 4,990 projects involving 3,331 UK firms. In order to combine it with firm-level data we exploited the information on firms' names and addresses provided in the dataset. Firms' names and addresses have been matched by the UK ONS to the Inter Departmental Business Register (IDBR) in order to provide a list of anonymized firms' identifiers. Notwithstanding a number of potential matching issues, such as incorrect spelling of names and addresses, changes of names and companies stopping reporting any economic activity, a unique identifier has been retrieved for almost half of the sample (1,488 firms; 45%).[3]

Through the unique identifier provided by the ONS, we could link our data to two main sources of data: the Business Structure Database (BSD), which provides basic information about firms (e.g. employment, turnover, industry classification codes and location), and the Business Expenditure on R&D database (BERD), providing R&D data collected through an annual survey carried out by the ONS. The BERD data uniquely provides information on total R&D expenditure in the UK by business enterprises and total R&D employment. After we match the data on U-I partnerships to firm-level data via firms' unique identifier, we keep non matched observations with non-missing values in both BSD and BERD variables. The non-matched observations form the pool of potential untreated firms. Therefore, linking U-I partnerships with firm-level data allows to work in a situation that is typical of evaluation studies (with observational data), in which it is possible to separate firms on the basis of the receipt of the treatment.

2.4 Method

2.4.1 The evaluation problem

The evaluation of publicly funded U-I partnerships should take into account the potential selection bias of the policy. This arises from the fact that firms are selected into treatment by the funding agency (hence not randomly), most likely on the basis of a number of peculiar characteristics and probably with a 'picking the winner' or 'aiding the poor' strategy. In addition, a bias might as well come from the firm side: some firms can in fact have advantages over other firms to search and find funding opportunities, either because of their past experience or because of their intrinsic characteristics, or both. As a consequence, treated and non-treated

[3]We carried out a sample representativeness analysis by comparing project related variables between the group of matched firms (1,488 firms) and the initial sample (3,331 firms) as well as between the former and the group of unmatched firms (1,843 firms). It emerges that matched firms display very similar or slightly lower figures than the full sample, hence we are confident that matched firms do not represent a selected sample of the latter. See Appendix 2.9.1, table 2.13 columns (a)-(e).

firms would behave differently notwithstanding the treatment, thus the simple difference in means in their performance after the treatment cannot be interpreted as causal impact.

The challenge is that it is impossible to carry out a counter-factual analysis by comparing the performance of participants (or treated) firms with the case of the same firms not receiving the treatment. Similarly, it is highly unlikely that researchers are able to carry out an experiment in which treated and non-treated firms are perfectly randomized and hence their mean performance can be compared after the treatment. In addition, very rarely the list of firms that applied to the R&D programme but have been rejected is available to the researcher.[4]

As suggested by Almus and Czarnitzki (2003), the best solution at hand when working with non-experimental data is to work as if we are in a quasi-experimental setting, in which a potential control group of non-treated firms is made statistically identical to the group of treated firms via propensity score matching (PSM). PSM is a matching technique that attempts to estimate the impact of a treatment by accounting for the factors that predict the receipt of the treatment (Caliendo and Kopeinig, 2008).

Therefore, in order to assess the impact of EPSRC U-I research projects on participating firms and tackle the issue of selection bias of the policy, we first select a control group of untreated firms on the basis of pre-treatment characteristics via propensity score matching (PSM) and then compare the performance of treated and untreated firms via ordinary least squares (OLS) regression. Because of the characteristics of our data, we only use PSM to select a control group of non-participating firms and, instead of estimating the impact of the policy via PSM, we employ OLS regression to do that.[5]

Although firms may have participated to more than one project, we are interested in the impact of the first project only. In fact, we believe that, due to learning processes occurring during the implementation of a project, firms develop internal capabilities and experience so that following

[4]This limitation applies to our case.

[5]Section 2.4.4 provides further information on the reason for employing OLS regression.

projects may have an effect on R&D effort that is different from what we hypotesised. For this reason, we focus only on the impact of the first project. Each project lasts, on average, three years, hence we estimate the impact in the year right after the end of each project. Since firms in our sample may have taken part to a project in any year t between 1998 and 2007, we have to select an ad-hoc control group on the basis of pre-treatment characteristics that depends on the year of treatment. More specifically, we select a control group on the basis of pre-treatment characteristics in year $t-1$ and estimate the impact of the project at $t+3$. In other words, we will estimate the impact of U-I projects that started in 1998 on the basis of pre-treatment firms' characteristics measured in 1997, on R&D expenditure per employee and share of R&D employment in 2001, and so on for every year until 2007.

To implement our methodology we start by splitting the raw sample of participating firms (1,488) into 10 subsamples on the basis of the year of participation and match them to firm-level datasets to collect pre- and post-treatment variables as well as to attach non-treated firms. The final sample of treated firms consists of 370 firms who participated at least once to a U-I project between 1998 and 2007.[6] Secondly, we carry out a propensity score matching on every sub-sample with the aim of selecting ad-hoc controls for every group of firms. Once this is done, we pull the newly created sub-samples of treated and selected untreated firms back together. We thus end up with a pooled cross sectional dataset where a given firm is observed only in one point in time. We then estimate OLS regressions where the dependent variables are R&D expenditure per employee and share of R&D employment, and the participation to a U-I project is the independent or 'treatment' variable. By controlling for the year of receipt of the treatment, along with other control variables, we can get a reliable estimate of the impact of U-I projects on participating firms.

[6] We carried out a sample representativeness analysis by comparing project related variables between the group of 370 treated firms and the whole sample of treated (3,331) (see Appendix 2.9.1, table 2.13 columns (f)-(g)). Treated firms are not different from the whole sample and, where significant differences exist, these are fairly small.

2.4.2 Propensity Score Matching

In the recent innovation literature that focuses on the impact of R&D subsidies, there have been several attempts to address the issue of selection bias of the subsidies by employing matching estimators (see e.g. Almus and Czarnitzki, 2003; Czarnitzki and Licht, 2006; Aerts and Schmidt, 2008; Corsino et al., 2012; Guerzoni and Raiteri, 2012).[7]

PSM consists of finding a plausible control group of non-treated firms that are similar to the treated ones in pre-treatment characteristics and using this group as a substitute for non-observable counterfactuals to estimate the impact of a given policy (Caliendo and Kopeinig, 2008). Treated observations are matched with non-treated ones on the basis of the so-called propensity score, $P(X) = P(D = 1 \mid X)$, defined as the probability of being treated (treatment $D = 1$) given a set of pre-treatment characteristics X. To consistently carry out a propensity score matching, two assumptions must be satisfied. The first is the Conditional Independence Assumption (CIA), or unconfoundedness, stating that assignment to treatment is independent of the outcomes, given a set of observable covariates. In other words, the observables must account for all the differences related to the outcome between treated and control units. The second assumption, referred to as the Common Support Condition, ensures that the vector of covariates does not perfectly predict whether a firm receives or not the treatment.

The reason for implementing a PSM in our case is twofold. Firstly, after we combine the data on U-I partnerships with firm-level data, we are in a situation that is typical for evaluation because we are able to separate treated and non-treated firms. Furthermore, the group of non-treated is large enough to draw the control group on the basis of a propensity score. Secondly, given that a rich dataset of pre-treatment characteristics is available, we can implement the PSM and assume the CIA to hold.

[7] Almus and Czarnitzki (2003) apply propensity score matching to find a suitable control group for a sample of German firms that received R&D subsidies and end up with a complementarity effect of the subsidy with respect to private R&D. On the same vein, Czarnitzki and Licht (2006) indicate the additionality of R&D subsidies for Western and Eastern Germany, González and Pazó (2008) show the absence of a crowding-out effect of R&D subsidies in a sample of Spanish firms, and, more recently, Guerzoni and Raiteri (2012) show that the interaction of different policies (R&D subsidies and public procurement) has the highest impact on firms' R&D expenses and innovative turnover.

2.4.3 Propensity score specification and selection of control groups

The propensity score measures the probability that a firm enters a U-I project, given a set of observable characteristics. It is recovered through the estimation of a probabilistic choice model where the dependent variable is the treatment variable. Two decisions have to be made at this stage: the first one concerns the model to be estimated and the second one concerns the variables to be included in this model. As for the model, since for binary treatments a probit or a logit usually yield similar results (Caliendo and Kopeinig, 2008), we decided to implement a probit model, following existing empirical evidence (Almus and Czarnitzki, 2003). The choice of the variables to include in the model is very important and more advice is available in the literature. We refer here to the guidance provided by Caliendo and Kopeinig (2008) as well as to what has been done in the empirical literature on the evaluation of R&D policy.

The first important caveat is that all variables must be measured before the treatment takes place, or must be fixed in time, so that we can rule out the possibility that those are affected by the treatment, hence endogenous. We first discuss the variables measured before the treatment and then we illustrate those that are fixed in time.

We start by including in the vector of covariates an important set of factors that may positively influence both the participation to U-I projects and the outcome measures, which relate to firms' size and economic performance. We include in the probit estimation a measure of employment at $t-1$ as well as its square, in order to check for the existence of a quadratic relationship between size and participation. These variables capture the different behavior that firms of different size have with respect to R&D activities. Secondly, we introduce a measure of labour productivity at $t-1$, calculated as the logarithm of sales over employment, as well as a market share variable that measures competition in the market, calculated as firms' sales over industry's sales, measured on the SIC 5 digits level.

Due to missing values, we are not able to recover any other firm-level characteristic, such as export and import ratio or capital intensity as it is done in other works. However, we include a dummy indicating whether each firm's ultimate owner is a non-UK company, which is a proxy for the existence of linkages with foreign markets, and we control for whether each firm is a single or multi plant one, which may be informative of capital intensity as well as overall economic performance. In other empirical works a variable to control for whether firms carry out R&D is usually included. However, in our case this is not necessary because we are dealing with a sample of innovative firms only. In fact, the BERD survey, which represents our main source of data to build the outcome variables and select the control groups, only involves UK R&D doers.[8] Finally, we control for firms' age, through a set of dummies for the years of birth of each firm, to account for the fact that younger firms may be more involved than older firms into R&D activities, including collaboration with universities.

As for the variables that are fixed in time (all measured at $t-1$), we include a set of 35 dummies to control for industry determinants. We use the Standard Industrial Classification codes (SIC 1992) at two digits level.[9] These should pose no problems in terms of potential changes in time, being at two-digits. Industry dummies allow to match firms belonging to the same sectors, hence sharing the same (or very similar) technological base.

We also include dummies for the location of the firms, which are all UK based. After several trials and considerations, we decided to include 12 regions, these being the nine English regions[10] along with Wales, Scotland and Northern Ireland. The use of region dummies, rather than smaller geographical units, reduces problems due to firms that relocate; in fact, it is reasonable to assume that most of those that relocate are likely to move within the same region. By including these dummies, we aim at matching treated firms with non-treated firms that are located in the same region and thus are subject to similar external factors, such as local economic shocks. They also allow to account for the presence of universities, research centers and other institutions in the area where firms are located, which most likely influences the probability to join a U-I project. As it was un-

[8] However, the inclusion of performance-related measures together with industry dummies (proxy for firms' technology and knowledge base), should help capturing the R&D dimension at least partially, thus reducing concerns related to omitted variables.

[9] See Appendix 2.9.2.

[10] London (LON), South East (SE), South West (SW) East of England (EE), Yorkshire and The Humber (YH), West Midlands (WM), East Midlands (EM), North West (NW) and North East (NE).

derlined in section 2.2.3, at the time when the research partnerships under analysis were funded, a key role was assigned in the UK to universities and regional development agencies for the promotion of knowledge transfer in regions. Therefore, it is fundamental to take these factors into account.

Table 2.1 and Figure 2.1 describe the variables used to estimate the propensity score and refer to the sample of 370 participating firms, summed up to the raw sample of non-participating firms (126,221) that forms the potential control groups (Total 370+126,221=126,591). Descriptive statistics refer to the year before the treatment for each firm ($t-1$). We also test for the difference in means between treated and the raw sample of untreated firms.[11] Treated and untreated firms display statistically significant differences (both positive and negative) in their size (measured with employment), market share, foreign links and share of single-plant firms, whereas no significant differences exist in labour productivity and firms' age. The distribution of treated and untreated firms across UK regions shows some differences too, especially with respect to the South East, where treated firms are over represented with respect to untreated ones, and London, where it is the opposite.

As for the distribution across sectors (Figure 2.1), we notice a larger presence of treated firms in the manufacturing of radio and televisions, of chemical products and of medical products. Untreated firms are overrepresented in service sectors such as wholesale trade, research & development activities and business activities (e.g. legal, accounting, intellectual property rights and other management activities). These descriptives show that treated firms and the raw group of untreated firms are quite different as far as their pre-treatment characteristics are concerned, thus supporting the need to select an ad hoc control group that is as similar as possible to the treated group.

As previously illustrated, after we split the sample into 10 sub-samples and attach potential controls on the basis of the year of participation, we estimate a probit model on each of them. The dependent variable is the treatment variable, so that what we estimate is the probability of receiving

[11] We do not report figures for industry dummies but differences between treated and untreated firms in sectoral composition can be visually analysed in Figure 2.1. The full list of industry SIC codes and description can be found in Appendix 2.9.2.

the treatment, or the so-called propensity score, which we use to select 10 ad-hoc control groups of untreated firms. The results of the probit estimations carried out on each of the 10 sub-samples are summarised in table 2.2.[12]

In the first place, as expected, it emerges that firm size is positively related to participation to U-I R&D projects since the employment variable is positive and significant across almost all the estimations. In addition, a quadratic relationship between participation and number of employees emerges in some of the estimations, since the coefficient for the square of the employment is negative and significant. Such relationship implies that the probability of participation increases with firms' size, but it decreases after a given threshold. Therefore, medium-to-large firms arguably have higher probability of participating than very small and very large firms.

Secondly, the market share of firms positively and significantly affects the probability of participating to U-I R&D projects only in a few years, whereas labour productivity does not seem to matter significantly. Non-UK owned firms display higher probability of participation than UK-owned firms in few estimations, and single-plant firms seem to have lower probability than multi-plant ones (although not always significant). With respect to firms' age, as expected, older firms have lower probability than younger firms to participate. As far as sectors are concerned, firms in manufacturing generally have a higher probability of participating to U-I projects than firms in service sectors.

Finally, region dummies show quite heterogeneous patterns because of a mixture of positive and negative signs across years. In spite of the distribution of economic activities and universities in the UK, EPSRC funded U-I collaborations seem to involve firms that are spread across the territory, rather then being agglomerated in some areas.

With the estimated propensity scores at hand we can match treated and untreated firms. It is possible to implement the pairing of treated to non-treated firms by using several matching algorithms. All of them are summarised and discussed by Caliendo and Kopeinig (2008). The choice of

[12]See Appendix 2.9.3 for the full results of the probit estimations.

a given algorithm with respect to another is a matter of trade-off between bias and variance of the estimates. In the first place, we implement a 1-to-1 nearest-neighbour matching according to which we match each treated firm to only one untreated firm, on the basis of similarity in their propensity score. In addition, we implement a number of different matching procedures to check the robustness of our findings. We follow Caliendo and Kopeinig (2008), who suggest that, if there are many comparable untreated units, it is advisable to use more than one nearest-neighbour to gain precision in the estimates. Hence, we implement a nearest neighbour matching with 5 and 10 untreated firms, in which each firm is matched to the 5 or 10 most similar ones in terms of propensity score, and a kernel matching that uses weighted averages of all (or nearly all) firms in the control group. With N:5, N:10 and Kernel matching a lower variance (than with 1:1 matching) is achieved, because more information is used (i.e. more than one control firm per treated firm), hence the estimates are more precise. On the other hand, it may be that observations that are bad matches are used, hence leading to a relatively higher bias.

We implement a 1:1, 1:5, 1:10 and kernel matching on each of the 10 subsamples of firms that start a U-I project in a year between 1998 and 2007, and we keep only treated firms and untreated firms that have been matched to them.[13] Table 2.3 shows the size of each sub-sample along with the size of the whole sample that we obtain by pulling everything back together before we estimate the impact of U-I projects. With 1:1 matching, we end up with a final sample of 740 observations, of which 340 are treated firms and 340 are untreated firms. We implement the matching without allowing to re-use the same untreated observation more than once ('noreplacement'), so that each untreated firm is matched to only one treated firm. With 1:5 and 1:10 matching, we end up with 1,722 and 3,299 controls respectively. In this case, we allow for re-using the same untreated firm, hence the number of selected untreated firms does not round up to exactly 5 (and 10) times the number of treated because a few untreated firms are used more than once.[14] In the case of kernel matching, the final sample includes 370 treated firms and 55,690 untreated firms, because almost half of the observations of the raw sample of untreated are selected.

[13] We use the Stata command *psmatch2*, developed by Leuven and Sianesi (2012).

[14] A check of the matching procedure shows that there is no over use of the same controls in any of the estimates.

2.4.4 Impact of U-I projects

Once we pull together the 10 matched datasets, we can evaluate the impact of U-I projects on participating firms. In principle, we would like to replicate the PSM procedure on the whole sample in order to get an estimate of the average treatment effect on the treated. However, by doing so we would not be able to control for the participation year, hence this may result in the wrong pairing of treated firms that participate in a given year with untreated firms that have been previously selected to be control units for other years. Given the cross-sectional nature of the data, the best solution at hand is to run an OLS regression where we control for the participation year. By doing so, we make sure that each treated firm is compared to similar pre-selected untreated firm(s) within the same year t.[15]

In addition, we replicate the regression and add the same controls that we used to estimate the propensity score, so to make sure to get an unbiased estimate of the impact of the policy. By mixing propensity score matching with linear regression we aim at obtaining an estimate of the treatment effect that is 'doubly-robust' (Imbens, 2004). In our case, we carry out an OLS regression on the matched sample, in which for each treated firm, one (or more) suitable untreated firm has been previously selected via propensity score matching.

In the case of 1:1 matching, we run an OLS regression with robust standard error to account for heteroskedasticity of the error terms, as recommended by Angrist and Pischke (2008). In the case of 1:5, 1:10 and Kernel matching, we carry out a weighted OLS regression, in which we use the propensity score as weighting variable, so that each untreated firm is given a specific weight in the regression that depends upon its similarity to its matched treated firm. Since the propensity score recovered via PSM represents the probability that each firm is selected, we employ sampling (or probability) weights, which are weights that denote the inverse of the probability that the observation is included.[16]

[15] Another strategy to carry out the evaluation exercise and solve the selection bias issue would have been to implement fixed effect estimations. However, since the main data source for R&D related variables is the BERD survey, administered on a stratified sample of firms each year, it was very difficult to collect data on the same firm for more than a point in time. Therefore, the use of propensity score matching, and eventually its combination with OLS regression, is the best solution at hand.

[16] *pweights* in Stata: a robust variance estimation technique is automatically used to ad-

2.5 Results

2.5.1 Outcome variables

As explained in sections 2.2.4, we expect that EPSRC funded U-I projects have a direct impact on R&D input of firms. Therefore, we employ a measure of R&D expenditure per employee (henceforth $R\&D/empl$) in logarithm, calculated as R&D intramural expenditure on the number of R&D personnel. Intramural or in-house expenditure refers to the cost of R&D carried out within the company in the UK regardless of the source of funding for this work. R&D personnel indicates the number of full-time equivalent engineers, technicians and other supporting staff working on R&D related tasks within the company. We also employ a measure of the share of R&D employment (henceforth $shareR\&Dempl$), calculated as the ratio of R&D personnel over total employment. To build both measures, we use data from the BERD survey, which provides information on firms' R&D activities at the end of each financial year.

Table 2.4 shows the descriptive statistics for $R\&D/empl$ and $shareR\&Dempl$ in the four matched samples. We also test the significance of the difference in means between treated and untreated firms (last column). The mean value of the log of $R\&D/empl$ is in the region of 3.7-3.8, it is larger for treated than for untreated firms in each matched sample and the difference (between 0.08 and 0.14) is significant at 1-5% level.[17] As for $shareR\&Dempl$, firms in the whole samples employ, on average, 11.5-13.2% of their workforce on R&D related tasks, corresponding to 20-22 employees, and the difference between treated and untreated firms is 3.2-4.3% (significant at 1% level).

2.5.2 Description of results

The results of the OLS regressions are presented in tables 2.5, 2.6, 2.7 and 2.8. For every matching method implemented (1:1, 1:5, 1:10 and kernel) we estimate two OLS regressions for both outcome variables presented in

just for the design characteristics so that variances, standard errors and confidence intervals are correct.

[17]The corresponding non-logged mean is £53,000-57,000 in the whole sample (depending on the matching implemented), £60,000 in the sample of treated firms and £53,000 in the sample of untreated firms.

2.5.1: we first control only for the year of receipt of the treatment (columns (1) and (3)) and then include all the covariates previously used to estimate the propensity score (columns (2) and (4)). The overall result is that there is a positive and significant effect on both $R\&D/empl$ and $shareR\&Dempl$ and this is very similar and robust across different matched samples.

The impact of participation to U-I projects on firms' $R\&D/empl$ is in the region of 0.076-0.118, the lowest being found in the 1:5 matched sample and the highest in the kernel matched sample. These figures correspond to an increase in the $R\&D/empl$ of treated firms by 7.9-12.5% three years after the start of the projects.[18] Given that $R\&D/empl$ of treated firms is, on average, £60,000, participating to a U-I project has the effect of increasing it by around £4,740 (7.9%) - £7,500 (12.5%).

The impact of U-I projects on firms' $shareR\&Dempl$ is also positive and significant: participant firms employ, on average, 3-4% of R&D employees more than non-participants, three years after the start date of the project. This means that treated firms have, on average, 0.7-1 employee more after the treatment, given that 22 is the average number of R&D personnel in treated firms.

As hypothesised in this work, firms that participate to R&D projects with universities display higher figures as far as their R&D effort is concerned. In the first place, the exchange of knowledge and resources with university that arises from participation to U-I R&D projects has the effect of increasing R&D expenditure per employee, because it entails a higher firms' engagement in research, both in terms of knowledge production and financial engagement. Secondly, through the network of relationships that arise from the partnerships, U-I projects represent an opportunity for companies to hire new R&D personnel at the end of the project as well as the chance of learning for existing staff. Before discussing our findings, we dedicate the next section to assess the quality of the matching procedure that we implemented.

[18]The interpretation of the estimated coefficient of a dummy variable in a log-linear regression is calculated by taking the anti-log of the coefficient and subtracting 1 to that, so to find the estimated % change in the outcome variable (Halvorsen and Palmquist, 1980).

2.5.3 Evaluating the quality of PSM

In this work we implemented a propensity score matching in order to find a plausible control group of non-treated firms that are similar to the treated ones in pre-treatment characteristics. As shown in table 2.1 and Figure 2.1, pre-treatment characteristics differ quite substantially between treated and the raw group of untreated firms before the matching, hence supporting the need to select an ad-hoc control group. Therefore, for the matching procedure to be satisfactory, we expect that the mean values of the two groups for every single pre-treatment variable do not differ significantly after matching.

For every matching algorithm that we implement, we carry out a balance test of the covariates used in the estimation of the propensity score, by performing a *t-test* on the hypothesis that the mean value of each variable is the same in the treatment group and in the control group after the matching. The results are reported in Tables 2.9, 2.10, 2.11 and 2.12 . The last two columns of each table report the difference between the mean value of each variable in the treatment and control group and the T-statistics with the usual significance level.

The balance test on the 1:1 matched sample (Table 2.9) provides the best results, with the only exception of labour productivity and one of the industry dummies, which still display significant differences after the matching, but only at 10% level. Instead, it turns out that increasing the number of selected untreated matches with 1:5, 1:10 or kernel matching does not produce better matching on the covariates. The more controls are selected, the more covariates are not well balanced. This may be suggestive of the fact that observations that are bad matches are used, hence leading to a relatively higher bias. Therefore, we only consider the 1:1 nearest neighbour matching to be satisfactory in achieving a good balance of pre-treatment characteristics between treatment and control group. The other matching algorithms implemented yields very similar results in the OLS regressions, but are not fully satisfactory.

2.6 Discussion and conclusion

This paper has investigated the impact of university-industry R&D collaboration on firms' R&D effort. We estimate the effect that U-I partnerships funded by the EPSRC in the UK have on firms' R&D expenditure per employee and share of R&D employment. We hypothesise that the exchange of knowledge and resources with university has a positive effect on R&D expenditure per employee and that U-I projects provide the opportunity to hire new R&D personnel at the end of the project, hence increasing the share of R&D employment. To investigate this, we use a novel and unique dataset, made up of data on U-I partnerships combined with firm-level characteristics. We employ propensity score matching to select a control group of firms that is as similar as possible to the group of treated firms in terms of pre-treatment characteristics and we estimate the impact of U-I projects via OLS regression on the matched sample.

We find that EPSRC U-I collaborations funded between 1998 and 2007 have a positive impact on both intramural R&D expenditure per employee and share of R&D personnel employed, three years after the beginning of U-I projects. This result is very similar across several matching methods employed for the selection of the control group. The 1:1 nearest neighbour matching provides the most robust results because it achieves a satisfactory balance of the pre-treatment characteristics used to estimate the propensity score. From the OLS regression carried out on the 1:1 matches sample, it emerges that R&D expenditure per employee of participating firms increases by 8.37% after taking part to a U-I project, corresponding to £5,082.[19] The share of R&D employment increases by 3.43%, corresponding to, on average, 1 additional employee working on R&D related tasks after participation to a U-I project.

The results of this work are in line with previous empirical findings (see e.g. Becker and Peters, 2000; Becker, 2003; Lööf and Broström, 2008), as well as with the survey based study of ESPRC collaborations illustrated in Bruneel et al. (2009). However, they should be interpreted with caution because they represent average effects. In particular, this study has not investigated whether the results and their magnitude differ across firms (e.g.

[19] This is 8.37% of £60,711, that is the R&D per employee in the treatment group in the 1:1 matched sample.

size-groups and industries) and across time (e.g. short-term and long-term).

Yet, this study provides various contributions to the academic literature. Firstly, existing empirical evidence attempting to assess the impact of U-I interactions on firms is often vague about whether such impact should be traced on innovative activities or on the overall productivity. After a careful study of policy-related documents, we argue that, in our case, it is on the former, and in particular on the R&D input side, that an impact should be searched. This is due to the pre-competitive nature of the funded projects under study, which are aimed at contributing to upstream and basic research that is far from industrial application, hence far from producing R&D outputs. Secondly, we carry out our empirical exercise, on an original dataset, by combining propensity score matching and OLS regression in order to reduce the selection bias that is typical of evaluation studies in quasi-experimental settings, and our results are consistent across different matching procedures implemented. Although propensity score matching represents nowadays a standard methodology for policy evaluation, by combining it with OLS regression we obtain 'doubly-robust' estimates. Thirdly, we provide new evidence of the effect that EPSRC funded U-I research collaborations - extensively studied as far as their determinants and features are - have on firms, and we show that they have a positive impact on intramural R&D expenditure per employee and on the share of employees working on R&D related tasks.

As far as the policy discussion is concerned, our findings are supportive of the argument that universities are an integral part of the supply chain to firms to support business growth and economic prosperity both at the regional and national level. This was particularly emphasised in the UK policy discourse from the late 1990s onwards (Lawton Smith and Bagchi-Sen, 2006) and has been recently reaffirmed by the UK Wilson Review of Business-University Collaboration (Wilson, 2012). In particular, our result of a positive effect of U-I projects on firms' R&D employment is in line with Bruneel et al. (2009), who report that firms declared collaborating with university mostly to gain the opportunity to recruit appropriately trained staff. This leads to an important implication for science, technology and innovation policy. The main benefits of universities are certainly related to the expertise that they provide to the local economic system and this is often embodied in knowledge as well as people. Therefore, it is fundamental to create or strengthen (where they exist) mechanisms that support the use of university research as a mean for recruiting appropriately skilled staff, which are likely to be more useful than mechanisms focusing on research or recruitment alone (Bruneel et al., 2009).

To conclude, it is worth underlying that this work has some limitations, paving the way for further research. In the first place, in this study we focus on the impact of the first project entered by a firm and do not consider following projects. However, accounting for the number of U-I projects per firm could shed lights on differences between occasional participants and recurrent participants, both in terms of what determines participation and what its impact is. Secondly, it is worth noticing that, by only considering U-I partnerships funded by the EPSRC, we may only be capturing part of the story, given that firms generally receive a multitude of public funds (from different funding agencies) for R&D activities. However, the EPSRC funds the bulk of R&D activities in the UK (D'Este et al., 2013) and thus, we are confident that our case is quite representative. In addition, although we only focus on research collaboration as a channel of knowledge transfer between university and industry, it is well known that cooperative research partnerships are among the most typical forms of U-I research collaborations (OECD, 1998; Fontana et al., 2006) and, indeed, they are one of the most frequent policy instruments towards U-I knowledge transfer put in place by policy-makers (OECD, 1998, 2002a; Fisher et al., 2009; D'Este and Iammarino, 2010).

2.7 Tables

Variable ($t-1$)	Mean	St. dev.	Min	Max	Mean treated	Mean untreat.	Diff.
employment	115.13	668.37	0	67,377	367.75	114.36	253.38***
empl sq	459,957	2.49e+07	0	4.54e+09	1,447,509	456,988	990,520
lab. product.	242.61	15,217.2	0	3,044,692	203.05	242.73	-39.67
market share	0.0069	0.0368	0	1	0.0269	0.0069	0.0200***
foreign link	0.2243	0.4171	0	1	0.3159	0.2238	0.0921***
single plant	0.8096	0.3926	0	1	0.6553	0.8091	-0.1537***
birth year	1988.02	9.1905	1973	2006	1986.98	1988.03	-1.0537
East Midlands	0.0766	0.2659	0	1	0.0783	0.0765	0.0017
East of Engl.	0.1090	0.3117	0	1	0.1305	0.1089	0.0215
London	0.1109	0.3140	0	1	0.0731	0.1110	-0.0379**
North East	0.0306	0.1723	0	1	0.0261	0.0306	-0.0045
North West	0.0983	0.2978	0	1	0.0966	0.0983	-0.0017
N. Ireland	0.0212	0.1441	0	1	0.0261	0.0212	0.0048
Scotland	0.0843	0.2778	0	1	0.0731	0.0842	-0.0111
South East	0.1694	0.3751	0	1	0.2454	0.1692	0.0762***
South West	0.0822	0.2747	0	1	0.0652	0.0823	-0.0171
Wales	0.0501	0.2182	0	1	0.0391	0.0501	-0.0109
West Midlands	0.0877	0.2829	0	1	0.0783	0.0877	-0.0094
Yorks&Humb	0.0792	0.2701	0	1	0.0678	0.0793	-0.0114

Significance level: *** p<0.01, ** p<0.05, * p<0.1

Table 2.1: Descriptive statistics and mean comparison of pre-treatment characteristics between treated ($N = 370$) and untreated (raw sample: $N = 126,371$) firms

Variable	Sign and significance
employment	positive across all years, significant in most years
employment squared	negative across all years, significant in half of the estimations
labour productivity	mostly positive sign, never significant
market share	positive across almost all years, significant in few of the estimations
foreign link	positive and significant in few estimations
single plant	mostly negative, not significant
birth year	earlier birth years negative and significant
region dummies	mixture of positive/negative signs
industry dummmies	positive and significant for manufacturing, negative for services

Table 2.2: Summary of probit regressions estimating the probability of treatment in years 1998-2007

Year	(a) Treated	(b) Raw untreat.	(c) 1:1 psm untreat.	(d) 1:5 psm untreat.	(e) 1:10 psm untreat.	(f) Kernel psm untreat.
1998	35	7,559	35	167	318	5,257
1999	35	9,586	35	161	307	4,250
2000	61	8,251	61	278	531	6,096
2001	55	9,833	55	252	482	7,007
2002	31	11,148	31	140	272	4,320
2003	28	14,543	28	137	258	4,596
2004	43	17,759	43	195	371	8,479
2005	23	14,743	23	101	198	3,272
2006	39	16,612	39	192	373	7,980
2007	20	16,337	20	99	189	4,163
Total	370	126,371	370	1,722	3,299	55,690

Table 2.3: Distribution of treated (a) and raw untreated (b) firms across years and matching algorithms (c-d-e-f).

Outcome variable	Obs.	Mean	St. dev.	Min	Max	Mean treated	Mean untreat.	Diff.
1:1 psm								
ln R&D per empl$_{t+3}$	740	3.89	0.5035	0.4055	7.3455	3.9322	3.8463	0.0858**
share R&D empl$_{t+3}$	740	0.1323	0.1875	0.0003	1	0.1542	0.1104	0.0437***
1:5 psm								
ln R&D per empl$_{t+3}$	2,092	3.8537	0.4995	0	7.417	3.9343	3.8362	0.0981***
share R&D empl$_{t+3}$	2,092	0.1193	0.1704	0.0001	1	0.1534	0.112	0.0414***
1:10 psm								
ln R&D per empl$_{t+3}$	3,669	3.8340	0.4977	-1.6094	7.4171	3.9343	3.8227	0.1116***
share R&D empl$_{t+3}$	3,669	0.1154	0.1668	0.0001	1	0.1534	0.1111	0.0423***
kernel psm								
ln R&D per empl$_{t+3}$	56,060	3.7851	0.4388	-1.6094	9.3115	3.9312	3.7841	0.1470***
share R&D empl$_{t+3}$	56,060	0.1228	0.1685	1.35e-05	1	0.155	0.1226	0.0323***

Significance level: *** p<0.01, ** p<0.05, * p<0.1

Table 2.4: Descriptive statistics of the outcome variables for every matched sub-sample (1:1, 1:5, 1:10, kernel)

	(1) $lnR\&D/empl_{t+3}$	(2) $lnR\&D/empl_{t+3}$	(3) $\%R\&Dempl_{t+3}$	(4) $\%R\&Dempl_{t+3}$
Treatment$_t$	0.0859**	0.0804**	0.0438***	0.0343***
	(0.0367)	(0.0330)	(0.0136)	(0.0118)
Constant	3.723***	4.038***	0.174***	0.0226
	(0.0566)	(0.186)	(0.0334)	(0.0672)
Year dummies	yes	yes	yes	yes
Firm-level vars$_{t-1}$	-	yes	-	yes
Birth year dummies	-	yes	-	yes
Industry dummies	-	yes	-	yes
Region dummies	-	yes	-	yes
Observations	740	740	740	740
Adj-R2	0.0163	0.203	0.0198	0.273

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.5: OLS on 1:1 NN matched sample

	(1)	(2)	(3)	(4)
	$lnR\&D/empl_{t+3}$	$lnR\&D/empl_{t+3}$	$\%R\&Dempl_{t+3}$	$\%R\&Dempl_{t+3}$
Treatment$_t$	0.0821***	0.0762***	0.0409***	0.0399***
	(0.0280)	(0.0247)	(0.0119)	(0.0099)
Constant	3.687***	3.719***	0.170***	0.170***
	(0.0422)	(0.211)	(0.0283)	(0.0618)
Year dummies	yes	yes	yes	yes
Firm-level vars$_{t-1}$	-	yes	-	yes
Birth year dummies	-	yes	-	yes
Industry dummies	-	yes	-	yes
Region dummies	-	yes	-	yes
Observations	2,092	2,092	2,092	2,092
Adj-R2	0.0316	0.201	0.0255	0.292

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.6: Weighted OLS on 1:5 NN matched sample

	(1)	(2)	(3)	(4)
	$lnR\&D/empl_{t+3}$	$lnR\&D/empl_{t+3}$	$\%R\&Dempl_{t+3}$	$\%R\&Dempl_{t+3}$
Treatment$_t$	0.0949***	0.0872***	0.0429***	0.0393***
	(0.0267)	(0.0231)	(0.0115)	(0.0093)
Constant	3.705***	3.687***	0.174***	0.136***
	(0.0387)	(0.192)	(0.0277)	(0.0461)
Year dummies	yes	yes	yes	yes
Firm-level vars$_{t-1}$	-	yes	-	yes
Birth year dummies	-	yes	-	yes
Industry dummies	-	yes	-	yes
Region dummies	-	yes	-	yes
Observations	3,669	3,669	3,669	3,669
Adj-R2	0.0311	0.199	0.0291	0.296

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.7: Weighted OLS on 1:10 NN matched sample

	(1)	(2)	(3)	(4)
	$lnR\&D/empl_{t+3}$	$lnR\&D/empl_{t+3}$	$\%R\&Dempl_{t+3}$	$\%R\&Dempl_{t+3}$
Treatment$_t$	0.118***	0.0854***	0.0358***	0.0408***
	(0.0259)	(0.0224)	(0.0113)	(0.0096)
Constant	3.677***	3.703***	0.200***	0.0730
	(0.0354)	(0.0851)	(0.0270)	(0.0474)
Year dummies	yes	yes	yes	yes
Firm-level vars$_{t-1}$	-	yes	-	yes
Birth year dummies	-	yes	-	yes
Industry dummies	-	yes	-	yes
Region dummies	-	yes	-	yes
Observations	56,060	56,060	56,060	56,060
Adj-R2	0.0445	0.234	0.0342	0.329

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.8: Weighted OLS on kernel matched sample

Variable	Mean treated	Mean untreated	Diff.	T-stat
employment	361.93	309.01	52.92	0.71
empl. squared	1450000	821000	626537	0.86
labour productivity	181.23	115.27	65.96	1.64*
market share	0.03	0.03	0.00	-0.28
single plant	0.66	0.70	-0.04	-1.02
foreign link	0.31	0.33	-0.02	-0.55
birth year	1987.08	1986.53	0.55	0.85
East Midlands	0.08	0.08	0.00	0.00
East of England	0.14	0.13	0.00	0.11
London	0.07	0.05	0.02	1.41
North East	0.02	0.02	0.01	0.50
North West	0.09	0.10	-0.01	-0.37
North Ireland	0.02	0.02	0.00	-0.25
Scotland	0.08	0.08	0.00	-0.14
South East	0.25	0.28	-0.03	-0.91
South West	0.07	0.06	0.01	0.61
Wales	0.04	0.05	-0.02	-1.05
West Midlands	0.08	0.06	0.01	0.72
Yorkshire & Humberside	0.06	0.06	0.00	0.15
10	0.00	0.00	0.00	1.00
11	0.01	0.00	0.00	0.58
12	0.01	0.02	-0.01	-1.01
13	0.01	0.00	0.01	1.74*
14	0.00	0.00	0.00	0.00
15	0.00	0.00	0.00	0.00
16	0.00	0.00	0.00	0.00
17	0.01	0.01	0.00	0.45
18	0.01	0.00	0.01	1.00
19	0.00	0.00	0.00	1.00
20	0.09	0.09	0.00	0.00
21	0.03	0.03	0.01	0.43
22	0.02	0.04	-0.01	-1.11
23	0.02	0.03	-0.01	-0.48
24	0.04	0.02	0.01	1.06
25	0.08	0.06	0.02	1.03
26	0.02	0.01	0.01	1.01
27	0.05	0.07	-0.02	-1.24
28	0.06	0.06	0.00	-0.15
29	0.12	0.14	-0.02	-0.66
30	0.03	0.03	0.00	0.00
31	0.01	0.01	0.00	0.00
32	0.02	0.02	0.00	0.00
33	0.00	0.00	0.00	1.00
34	0.01	0.02	-0.01	-0.64
35	0.00	0.01	0.00	-0.58
36	0.03	0.03	0.00	-0.21
37	0.01	0.00	0.01	1.42
40	0.00	0.00	0.00	1.00
41	0.00	0.00	0.00	0.00
45	0.01	0.00	0.01	1.00
50	0.11	0.11	0.00	0.00
51	0.08	0.08	0.00	0.00
52	0.10	0.10	0.00	0.12
55	0.00	0.01	-0.01	-1.42
60	0.01	0.01	0.00	0.38
61	0.01	0.02	-0.01	-0.91

Significance level: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2.9: Mean comparison and T-test after 1:1 matching (N *treated* $= 370$, N *untreated* $= 370$)

Variable	Mean treated	Mean untreated	Diff.	T-stat
employment	370.76	249.25	121.51	2.71***
empl. squared	1479399	519435	959963	2.59***
labour productivity	205.32	169.54	35.78	0.58
market share	0.03	0.02	0.01	1.79*
single plant	0.66	0.69	-0.04	-1.36
foreign link	0.31	0.31	0.00	-0.01
birth year	1987.00	1986.68	0.32	0.62
East Midlands	0.08	0.08	0.00	-0.08
East of England	0.13	0.14	0.00	-0.19
London	0.07	0.07	0.00	0.05
North East	0.03	0.02	0.01	1.30
North West	0.09	0.10	-0.01	-0.37
North Ireland	0.02	0.03	0.00	-0.52
Scotland	0.08	0.07	0.01	0.50
South East	0.25	0.26	0.00	-0.18
South West	0.07	0.06	0.00	0.19
Wales	0.04	0.05	-0.01	-0.97
West Midlands	0.08	0.07	0.01	0.63
Yorkshire & Humberside	0.06	0.06	0.00	0.17
10	0.00	0.00	0.00	0.71
11	0.01	0.00	0.00	1.30
12	0.01	0.01	-0.01	-0.98
13	0.01	0.01	0.00	0.66
14	0.00	0.00	0.00	0.38
15	0.00	0.00	0.00	0.38
16	0.00	0.00	0.00	0.38
17	0.01	0.01	0.00	0.50
18	0.01	0.01	0.00	0.36
19	0.01	0.00	0.00	1.69*
20	0.09	0.09	0.00	0.00
21	0.03	0.03	0.00	0.52
22	0.02	0.02	0.00	0.00
23	0.02	0.02	0.00	-0.27
24	0.04	0.03	0.01	0.62
25	0.08	0.07	0.01	0.59
26	0.02	0.01	0.00	0.71
27	0.05	0.06	-0.01	-0.73
28	0.06	0.06	0.00	-0.13
29	0.12	0.12	-0.01	-0.32
30	0.03	0.02	0.01	0.71
31	0.01	0.01	0.00	0.40
32	0.02	0.02	0.00	-0.39
33	0.00	0.00	0.00	1.19
34	0.01	0.01	0.00	-0.48
35	0.00	0.00	0.00	-0.39
36	0.03	0.04	-0.01	-0.66
37	0.01	0.01	0.00	-0.74
40	0.00	0.00	0.00	-0.07
41	0.00	0.00	0.00	0.13
45	0.01	0.00	0.01	1.46
50	0.11	0.12	-0.01	-0.47
51	0.08	0.08	0.00	0.26
52	0.10	0.10	0.00	-0.09
55	0.00	0.00	0.00	-0.66
60	0.01	0.01	0.00	-0.56
61	0.01	0.01	0.00	-0.48

Significance level: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2.10: Mean comparison and T-test after 1:5 matching (N *treated* $= 370$, N *untreated* $= 1,722$)

Variable	Mean treated	Mean untreated	Diff.	T-stat
employment	370.76	233.03	137.73	3.48***
empl. squared	1479399	484778	994621	3***
labour productivity	205.32	158.05	47.27	0.85
market share	0.03	0.02	0.01	2.63***
single plant	0.66	0.70	-0.04	-1.54
foreign link	0.31	0.31	0.01	0.37
birth year	1987.00	1986.72	0.28	0.57
East Midlands	0.08	0.08	0.00	-0.02
East of England	0.13	0.14	-0.01	-0.28
London	0.07	0.07	0.00	0.30
North East	0.03	0.02	0.01	1.21
North West	0.09	0.11	-0.01	-0.66
North Ireland	0.02	0.02	0.00	-0.04
Scotland	0.08	0.07	0.00	0.03
South East	0.25	0.24	0.01	0.47
South West	0.07	0.06	0.01	0.62
Wales	0.04	0.05	-0.01	-0.77
West Midlands	0.08	0.08	-0.01	-0.36
Yorkshire & Humberside	0.06	0.07	0.00	-0.12
10	0.00	0.00	0.00	0.99
11	0.01	0.00	0.00	1.20
12	0.01	0.01	0.00	-0.55
13	0.01	0.01	0.00	-0.02
14	0.00	0.00	0.00	0.73
15	0.00	0.00	0.00	-0.21
16	0.00	0.00	0.00	0.10
17	0.01	0.01	0.00	0.63
18	0.01	0.01	0.00	0.31
19	0.01	0.00	0.00	1.62
20	0.09	0.09	0.00	-0.31
21	0.03	0.03	0.00	0.01
22	0.02	0.02	0.00	0.15
23	0.02	0.02	0.00	-0.29
24	0.04	0.03	0.00	0.28
25	0.08	0.08	0.00	-0.01
26	0.02	0.01	0.00	0.55
27	0.05	0.05	0.00	-0.29
28	0.06	0.06	0.00	0.19
29	0.12	0.12	-0.01	-0.35
30	0.03	0.02	0.00	0.35
31	0.01	0.01	0.00	0.62
32	0.02	0.02	0.00	-0.12
33	0.00	0.00	0.00	1.33
34	0.01	0.02	-0.01	-0.79
35	0.00	0.00	0.00	-0.58
36	0.03	0.03	0.00	-0.30
37	0.01	0.01	0.00	-0.63
40	0.00	0.00	0.00	-0.01
41	0.00	0.00	0.00	0.22
45	0.01	0.00	0.01	1.55
50	0.00	0.00	0.00	-0.34
51	0.11	0.11	0.00	-0.11
52	0.08	0.08	0.00	0.34
55	0.10	0.10	0.00	-0.07
60	0.00	0.00	0.00	-0.47
61	0.01	0.02	0.00	-0.67
62	0.01	0.01	0.00	0.08

Significance level: *** p<0.01, ** p<0.05, * p<0.1

Table 2.11: Mean comparison and T-test after 1:10 matching (N $treated = 370$, N $untreated = 3,299$)

Variable	Mean treated	Mean untreated	Diff.	T-stat
employment	332.85	94.55	238.30	10.46***
empl. squared	1131392	193366	938026	1.34
labour productivity	181.65	220.08	-38.43	-0.05
market share	0.02	0.01	0.02	9.47***
single plant	0.67	0.83	-0.16	-8.16***
foreign link	0.32	0.20	0.12	5.57***
birth year	1987.15	1987.86	-0.71	-1.49
East Midlands	0.08	0.08	0.00	-0.23
East of England	0.14	0.13	0.01	0.58
London	0.07	0.11	-0.03	-2.17***
North East	0.02	0.02	0.01	1.02
North West	0.09	0.10	-0.01	-0.39
North Ireland	0.02	0.01	0.01	1.26
Scotland	0.08	0.08	-0.01	-0.55
South East	0.25	0.20	0.05	2.58***
South West	0.07	0.07	0.00	0.04
Wales	0.04	0.04	0.00	-0.28
West Midlands	0.08	0.10	-0.02	-1.28
Yorkshire & Humberside	0.07	0.07	0.00	-0.34
10	0.00	0.00	0.00	-0.08
11	0.00	0.00	0.00	2.01**
12	0.00	0.00	0.00	-0.08
13	0.00	0.00	0.00	-0.08
14	0.01	0.00	0.01	4.66***
15	0.01	0.02	-0.01	-1.19
16	0.01	0.01	0.00	0.34
17	0.00	0.00	0.00	-0.39
18	0.00	0.00	0.00	1.82*
19	0.00	0.00	0.00	1.73*
20	0.01	0.00	0.01	1.83*
21	0.01	0.01	0.00	-0.19
22	0.00	0.00	0.00	-0.27
23	0.09	0.05	0.04	3.06***
24	0.03	0.03	0.00	-0.17
25	0.02	0.01	0.01	1.51
26	0.02	0.01	0.01	3.30***
27	0.04	0.04	0.00	0.08
28	0.08	0.09	-0.01	-0.86
29	0.02	0.01	0.01	2.47***
30	0.05	0.04	0.01	0.76
31	0.06	0.02	0.04	4.62
32	0.12	0.06	0.06	5.37***
33	0.03	0.01	0.01	2.08**
34	0.01	0.00	0.01	2.36***
35	0.02	0.02	0.00	-0.26
36	0.00	0.00	0.00	7.01***
37	0.01	0.01	0.00	-0.03
40	0.00	0.00	0.00	0.18
41	0.03	0.09	-0.06	-4.04***
45	0.01	0.01	0.00	-0.34
50	0.00	0.00	0.00	-0.08
51	0.00	0.00	0.00	0.34
52	0.00	0.00	0.00	0.88
55	0.01	0.00	0.01	3.15***
60	0.00	0.00	0.00	-0.20
61	0.00	0.00	0.00	-0.18
62	0.00	0.00	0.00	-0.27
63	0.00	0.00	0.00	-0.11
64	0.11	0.11	0.00	-0.20
65	0.08	0.15	-0.06	-3.50***
66	0.10	0.18	-0.08	-4.02***
67	0.00	0.00	0.00	-0.57
70	0.00	0.00	0.00	-0.18
71	0.00	0.00	0.00	-0.08
72	0.01	0.01	0.00	0.47
73	0.01	0.01	0.00	1.17

Significance level: *** p<0.01, ** p<0.05, * p<0.1

Table 2.12: Mean comparison and T-test after Kernel matching ($N\ treated = 370$, $N\ untreated = 55,690$)

2.8 Figures

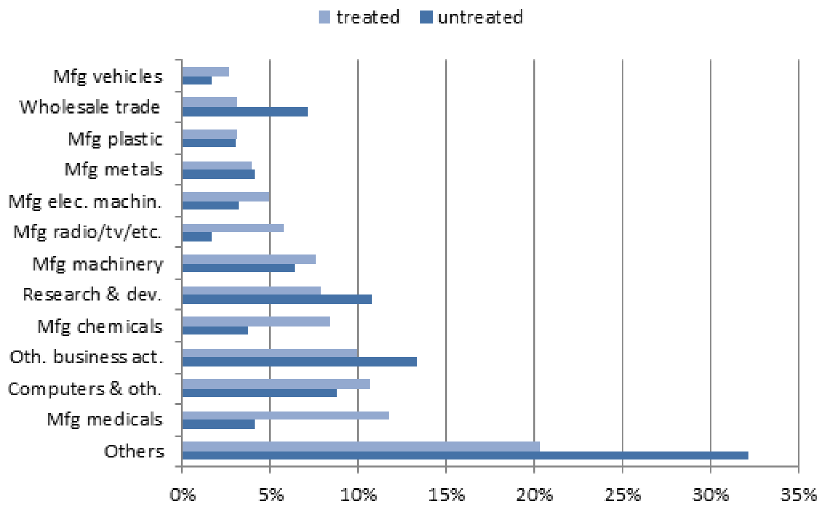

Figure 2.1: Distribution of treated and untreated firms across sectors (SIC 1992)

2.9 Appendices

2.9.1 Appendix: Sample representativeness

	(a) Mean full sample	(b) Mean unmatched	(c) Mean matched	(d) Diff. (b)-(c)	(e) Diff. (a)-(c)	(f) Mean matched	(g) Diff. (a)-(f)
	N=3331	N=1843	N=1488			N=370	
Num of prj	1.498	1.544	1.4401	0.1045**	0.0579**	1.5229	-0.0249
Lenght of prj, y	2.7553	2.7972	2.7035	0.0937**	0.0518**	2.6932	0.0621
Lenght of prj, d (ln)	6.8128	6.8336	6.7872	0.0464**	0.0256*	6.7829	0.0299
Funds per firm (ln)	9.6831	9.6957	9.6674	0.0282	0.0157	9.8133	-0.1302*
Share intra reg. U	0.2908	0.2791	0.3049	-0.0255*	-0.0141	0.3032	-0.0124
Size of U dept	42.8339	43.3462	42.2029	1.1433	0.631	42.8451	-0.0112
Quality of U dept	2.5496	2.5649	2.5307	0.0342	0.0189	2.5926	-0.043

Significance level: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2.13: Sample representativeness for projects characteristics

2.9.2 Appendix: Industries

Code	SIC 1992 description
10	Mining of coal & lignite, extraction of peat
11	Oil & gas extraction
14	Other mining & quarrying
15	Mfg of food products & beverages
16	Mfg of tobacco products
17	Mfg textiles
18	Mfg of wearing apparel
19	Tanning & dressing of leather
20	Mfg of wood & of products of wood & cork
21	Mfg of pulp, paper & paper products
22	Publishing, printing & reproduction of recorded media
23	Mfg of coke, refined petroleum products & nuclear fuel
24	Mfg of chemicals and chemical products
25	Mfg of rubber & plastic products
26	Mfg of other non-metallic mineral products
27	Mfg of basic metals
28	Mfg of fabricated metal products, except machinery & equipment
29	Mfg of machinery & equipment not elsewhere classified
30	Mfg of office machinery & computers
31	Mfg of electric machinery & apparatus not elsewhere classified
32	Mfg of radio, tv & communications equipment & apparatus
33	Mfg of medical, precision & optical instruments, watches & clocks
34	Mfg of motor vehicles, trailers & semi-trailers
35	Mfg of other transport equipment
36	Mfg of furniture & other not elsewhere classified
37	Recycling
45	Construction
50	Sale, maintenance & repair of motor vehicles & motorcycles; retail sale of automotive fuel
51	Wholesale & commission trade, except motor vehicles & motorcycles
52	Retail trade, except of motor vehicles & motorcycles
55	Hotels & restaurants
60	Land transport; transport via pipelines
62	Air transport
64	Post & telecommunications
65	Financial intermediation, except insurance and pension funding
71	Renting of machinery & equipment without operator and of personal and household goods
72	Computer & related activities
73	Research & development
74	Other business activities
85	Health & social work
92	Relational, cultural & sporting activities
93	Other service activities

Table 2.14: 2 digit Standard Industrial Classification 1992 codes and description

2.9.3 Appendix: Probit estimations

year	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
employment	0.000446	0.000674***	0.000332*	0.00223***	0.000210	0.00163**	0.00113***	0.00214**	0.000291	0.00233**
empl. squared	-1.37e-07	-5.16e-08**	-1.94e-08	-1.45e-06**	-4.27e-09	-8.10e-07*	-2.18e-07**	-7.48e-07	-2.48e-08	-1.10e-06*
labour productivity	-0.000112	7.11e-05	-8.01e-05	6.61e-05	9.24e-08	1.46e-05	-0.000159	-2.44e-05	5.14e-05	6.27e-05
market share	1.784*	-2.843	0.732	1.361	0.685	3.583**	0.506	-1.725	0.555	0.519
single plant	-0.102	-0.319*	-0.192	0.0610	-0.265	-0.00793	0.0583	0.0462	-0.152	-0.0866
foreign link	0.236	-0.0883	0.214	0.0749	0.363*	-0.0289	0.244*	-0.131	0.366**	0.178
EM	0.184	0.0507	-0.529	-0.0259	0.0743	0.105	0.118	0.610*	-0.0937	0.367
EE	-0.426	-0.615	-0.172	0.273	-0.118	0.738*	-0.150	0.369	-0.329	0.214
LON	0.0150		-0.158	-0.193	-0.211	0.239	-0.104	-0.0690	0.162	
NE	0.0868	0.00836		0.0499	0.297		-0.119		0.166	
NW	0.309		0.0397	-0.0224	-0.303	0.767*			-0.190	0.189
NI	0.182	-0.169	-0.304	-0.0474	0.238	1.159**	-0.312		0.434	0.732
SCO	0.0247	-0.00737	0.111	-0.0850	0.0567	0.316	-0.186	0.0532	0.166	0.191
SE	0.163		0.226	0.0945	0.313	0.735*	-0.404	-0.0142	-0.179	0.136
SW	-0.186	-0.309	-0.191	0.328		0.748*	-0.133	0.144	0.0695	
WAL	-0.103	0.102	0.107	0.127	-0.0207		-0.131		-0.285	0.490
WM	0.317		-0.480	-0.239	0.304				-0.435	0.181
YH		-0.107					-0.290			
1973	-0.137	-0.0663	-0.737**	-0.777	-1.875***	-0.476	-0.678	-0.991*	-0.0361	-0.216
1974		0.551	0.0342	-0.438	-0.672					
1975				-0.483		0.180				
1976	0.0673	0.0962						0.279		
1977		-0.0603	-0.299			-0.0436	-0.376		0.0524	
1978	-0.0432		-0.288	-0.587			-0.506	0.551		
1979				-0.684	-0.876			0.135		0.0714
1980		0.0718	-0.256	-0.439	-0.703	-0.0582				
1981	-0.0288				-1.075*	-0.249			0.0293	

year	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
1982	-0.103	-0.277	-0.598	0.00823	-0.719			-0.174	0.00644	
1983	-0.320	0.0258	-0.108	-0.734	-0.857			-0.193		
1984	-0.291	-0.00179	-0.0264	-0.833		0.0285	-0.260	-0.297	0.00419	
1985	0.0260	-0.297	-0.380	-0.584	-1.242**		-0.332		-0.146	
1986			-0.304	-0.983	-0.818			0.137	-0.0784	0.124
1987	-0.285	-0.139	-0.224		-1.104*	0.251	-0.0511		0.248	
1988	-0.349		-0.834*	-0.688		0.176	-0.687		-0.0180	-0.154
1989	-0.375	-0.175	-0.0142	-0.827	-1.110*	-0.470	-0.573	-0.351	-0.0231	-0.243
1990	-0.00185	-0.127	-0.315	-0.469		-0.404			0.00868	
1991	-0.518	-0.384	-0.0201	-1.049*	-1.410**		-0.478	0.0353		
1992	-0.0982	-0.397	-0.455	-0.425	-1.470**			-0.0686	0.331	-0.258
1993	-0.218	-0.270	-0.235	-0.522	-1.075*		-0.351		-0.325	-0.355
1994	-0.240			-0.820	-1.004*	-0.0318	-0.315		-0.207	
1995	-0.0141	-0.111	-0.0200	-0.754		-0.0706	-0.135	-0.119	-0.0233	
1996		-0.0568	-0.518	-0.959	-0.800		-0.515		0.272	-0.0971
1997			-0.280	-0.640		-0.0969	-0.477	-0.0405	-0.105	
1998				-0.800		0.227	-0.206			
1999				-0.291		0.428	-0.239	-0.114		
2000					-1.252**		-0.240	0.0474		-0.0958
2001							0.0642			-0.0104
2002							-0.0643			-0.0354
2003									0.577	-0.0693
10				0.475						
14						0.373			-0.426	
15	-0.360			-0.673						
16									0.124	
18		0.134	-0.338							
19			0.215	0.566						
20	0.818									
21					0.136					0.742

year	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
22		0.235	-0.304			0.101			1.360	
23					-0.0104		-0.296	0.601*	0.413	
24	0.0707		0.504	-0.285		-0.0141		0.122	-0.159	
25	0.107	0.286	-0.305		-0.329	-0.0471	-0.198	0.562		-0.0510
26	0.0577	-0.202	-0.0435		0.201	0.701*	-0.281		0.479	0.367
27	0.542		-0.416		-0.0448	0.848*	-0.214		-0.265	0.743
28	0.158	0.691		-0.346	-0.399		0.0891	0.295	-0.280	0.0337
29	-0.0991		-0.0645	-0.0367	0.232	-0.0197				
30	0.715*	0.177	-0.438	-0.0532			-0.190	0.339	0.272	
31	-0.0604		-0.289	-0.217	-0.195	0.465	0.143	0.892**	0.180	0.464
32	0.548	0.241	-0.754	0.140		0.202	-0.226	0.356	0.451	0.475
33	0.495*	0.761**	0.137	0.0728	-0.199	0.186	-0.131			0.555
34	0.545	0.719**	-0.0385	-0.520		0.357	0.289		0.247	
35		0.164	-0.284							
36	0.358	0.394	-0.256	-0.525		0.278	0.360			
37			-0.721							
45				-0.256		0.224	1.431*			
50					-0.539		-0.128	-0.0911	-0.472	
51	0.0175			-0.689	-0.324	0.0129	0.0638			0.0844
52			-0.435				-0.645			0.409
55			-0.223						0.384	
62					0.141					
65			0.866				-0.0956			
71					0.0601			0.180	0.0796	
72	0.476*			0.102	-0.121				0.0244	0.152
73	-0.336	0.229	-0.959**	-0.337	-0.243	-0.106	-0.219		0.0771	0.329
74		-0.0274	-0.602*	-0.210			-0.150			
93			-0.193							

year	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Constant	-2.652***	-2.376***	-1.643***	-1.953***	-1.241*	-3.368***	-2.197***	-2.941***	-2.812***	-3.151***
Observations	5,679	4,366	6,227	7,161	4,698	4,703	9,207	3,314	8,080	4,217

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2.15: Probit estimations

Chapter 3

Organisational-level determinants of academic engagement with industry

3.1 Introduction

In the last decades universities have extended their entrepreneurial activity in many directions, including collaborating with industry in research projects, patenting and licensing, creating science parks, and promoting university spin-outs. In the academic literature, there is large evidence on university intellectual property activity (or commercialization) and academic entrepreneurship, but it is widely recognized that other types of U-I interaction are more pervasive, although less traceable (Perkmann et al., 2013). In particular, 'academic engagement' refers to inter-organisational collaboration that links universities with other organisations, especially firms. Therefore, academic engagement represents an alternative way to define U-I knowledge transfer, but it differs from the latter in that it is more focused on the university side.

In this paper, we focus on the factors that bring UK universities to engage in U-I research collaboration, a specific typology of university knowledge transfer activity that falls under the definition of academic engagement as well as under that of U-I knowledge transfer. We study the case of R&D projects that involve UK universities and firms, which have been funded by the Engineering and Physical Sciences Research Council (EPSRC) between 1992 and 2007. These were mainly aimed at basic and pre-competitive research activities and often involved financial contribution from the private partners.

There is an extensive empirical evidence on the determinants of U-I collaboration (see e.g. Schartinger et al., 2002; D'Este and Patel, 2007; D'Este and Iammarino, 2010; D'Este and Perkmann, 2011; D'Este et al., 2013), but very often the focus is on the occurrence and the frequency of U-I engagement, whereas the volume of financial resources involved is only rarely accounted for. Instead, the income that universities receive from their knowledge transfer activities may reflect the value that external partners place on the knowledge they receive from universities and thus provide a proxy of the value created through knowledge transfer (Rossi and Rosli, 2013).

One exception in the empirical literature is represented by Perkmann et al. (2011), who measure different forms of academic engagement with the amount of funding that UK universities receive by companies. On the same vein, in this paper we intend to overcome the above-mentioned limitation by measuring U-I collaboration with the amount of funding that companies provide to U-I research collaboration led by UK universities. However, in order to carry out a more fine-grained analysis we focus on the individual departments engaged in collaboration with firms rather than looking at universities. In addition, since we analyse the specific case of publicly funded U-I collaborations, we control for the amount of public funding for U-I collaboration. Accounting for that is highly relevant for policy because it helps shedding new lights on the factors that attract private funding for academic research.

Moreover, the role of individual-level factors is well explored in the literature, but evidence is scant when it comes to the organisational context in which academic engagement occurs, especially with respect to the characteristics and academic quality of university departments involved (Perkmann et al., 2013). It emerges from some studies that academic engagement is negatively associated with organisation-level research quality (Ponomariov, 2008), whereas the link is not clear in some other studies. A negative relationship between quality and academic engagement might be due to the possibility that the latter acts as a resource mobilization mechanisms for high-performing academics at low-ranked institutions (Perkmann et al., 2013).

As suggested by Perkmann et al. (2013) in their agenda for future research, studies should also focus on the characteristics and research standing of teams and departments rather than only on the role of individual-level determinants. We take on board this suggestion and intend to shed new light on the role of organisation-level research quality by answering the following research question: *'What is the role of department level characteristics for UK universities' engagement in U-I collaboration?'*

Our analysis exploits a setting that is similar to the one used by Perkmann et al. (2011), in that we model university engagement with industry as depending upon research quality along with a number of features, but we take university departments as our unit of analysis. Moreover, we exploit a number of additional and crucial information on both academic engagement and research quality. In the first place, in our analysis we are able to account for past academic engagement and for past records of departmental research quality, which allows us to establish whether research quality plays a role and whether it still matters in the presence of past collaboration. Secondly, since we study the case of publicly funded U-I collaboration, we distinguish private and public contribution for academic engagement and we can thus check whether the relationship between industry funding and research quality is affected by the existence of past public funding. We believe this is relevant in light of the argument that public intervention may enhance or moderate the role of research quality for attracting private funding for research.

The paper is organised as follows: we review the relevant literature and develop our empirical hypotheses in section 3.2; in sections 3.3 and 3.4 we illustrate our data sources and methodology respectively; section 3.5 is dedicated to the description of the variables and the empirical results are presented in section 3.6; finally, we discuss our findings and offer some concluding remarks in section 3.7.

3.2 Literature and hypotheses development

3.2.1 The role of universities

In the last decades views changed regarding the role of universities in the economy: from being seen as 'ivory towers' where academics mainly performed research in isolation, universities became an economic organisation actively engaged with external stakeholders (Freitas et al., 2011). In order to compensate for the decrease in government funding for military-oriented research and for a more general reduction of government intervention in the economy, universities became more interested in collaborating with companies (Geuna and Muscio, 2009). In addition, due to competition pressures and increasing speed and complexity of knowledge processes, as well as declining profits and increasing costs of research, companies needed to get closer to external sources of knowledge in order to innovate. As a consequence, industry became increasingly interested in university research as well as highly skilled personnel to create and exploit new knowledge (Freitas et al., 2011).

Moreover, universities have assumed a territorial role that manifests itself in the stimulation of economic development through local spending on wages and services (Lawton Smith and Bagchi-Sen, 2012). This argument rests upon the assumption that university research promotes local knowledge spillovers which leads to regional innovation processes (Geuna and Muscio, 2009). In the analysis of knowledge spillovers as a source of innovation, productivity and growth, several levels of analysis have been accounted for. In the first place, various seminal contributions focus on the regional dimension of knowledge spillovers, showing that knowledge spillovers and innovative performance are geographically bounded (Jaffe, 1989; Audretsch and Feldman, 1996). Secondly, strong evidence emerges that there is a positive correlation between firms' geographical concentration and university location (Varga, 2000; Audretsch and Lehmann, 2005). Finally, recent literature investigates the effects of spillovers on urban productivity and city size (Henderson, 2007).

The common trait in all those studies is that firms are regarded as creative and dynamic agents, searching for knowledge in the local environment and that the spillovers of knowledge generate positive externalities to firms by stimulating innovation activities and productivity (Cassia et al., 2009). Inter-relations among firms, universities and research centres within economic systems are hence now considered vital for the generation and dissemination of new knowledge. Universities that are able to participate into the flows of knowledge interactions are crucial sources of external knowledge to firms. In addition, the shift towards the knowledge based model of economic development together with the paradigm of the 'entrepreneurial' university (Etzkowitz et al., 2000) legitimate universities to pursue their own profits, aside acting as a central agent in the process of knowledge production and generation (Lawton Smith and Bagchi-Sen, 2006).

As a consequence, nowadays many universities establish and nurture links with knowledge users, such as firms, and by facilitating technology transfer. Together with commercialisation activities, such as patenting and academic spinoffs, universities carry out a wide range of collaborating initiatives, identified as 'academic engagement'. As defined by Perkmann et al. (2013) 'academic engagement' refers to inter-organisational collaboration that links universities with other organisations, especially firms, and includes both formal activities (e.g. collaborative research, contract research and consulting) and informal activities like networking with practitioners. Although there is large evidence on university intellectual property activity and academic entrepreneurship, it is widely recognized that other academic engagement activities are more pervasive, but less traceable (Perkmann et al., 2013).

University-Industry collaborative (or cooperative) research is one specific channel of inter-organisational knowledge flows and potential spillovers from (and to) academic research aimed at carrying out R&D projects, mainly involving pre-competitive and basic research and often subsidized by public funding (OECD, 1998, 2002a; D'Este and Fontana, 2007; D'Este and Iammarino, 2010; D'Este et al., 2013). Cooperative research partnerships are among the most typical forms of U-I research collaborations, followed by contract research, research consortia, consulting and founding of co-operative research centres (OECD, 1998; Fontana et al., 2006). They also are one of the most frequent policy instruments put in place by local and national policy-makers to foster pre-competitive research and university-business knowledge transfer activities (OECD, 1998, 2002a; Fisher et al., 2009; D'Este and Iammarino, 2010).

Very often the focus of empirical research is on the realisation of partnerships and/or their number, measured by the occurrence and/or the frequency of U-I partnerships, whereas only rarely is the volume of financial resources deriving from collaborations accounted for. Rossi and Rosli (2013) argue that the income that universities receive from their knowledge transfer activities can reflect the value that external partners place on the knowledge they receive from universities and may provide a proxy for the value created through knowledge transfer. However, evidence is rather scant with respect to that. In this paper, we intent to fill this gap and therefore, we measure U-I collaboration by accounting for the income provided by companies involved in the partnerships, similarly to Perkmann et al. (2011), who operationalise academic engagement with industry using incomes derived from different forms of engagement.

3.2.2 The role of academic quality

There is extensive empirical evidence on the determinants of U-I collaboration (see e.g. Schartinger et al., 2002; D'Este and Patel, 2007; D'Este and Iammarino, 2010; D'Este and Perkmann, 2011; D'Este et al., 2013). In particular, the literature on university-business interactions has devoted a great deal of attention to the role of research quality. In their seminal contributions, Mansfield (1995, 1997) and Mansfield and Lee (1996) argue that academic research excellence is expected to be a strong driver for companies that are interested in carrying out joint research activities with universities. In the same vein, Tornquist and Kallsen (1994) show that high quality universities are likely to produce research with a greater potential for industrial application. More recently, it has been shown that university quality together with geographical proximity between businesses and universities influence the frequency of U-I collaboration in the UK (D'Este and Iammarino, 2010; Laursen et al., 2011).

Within the literature on the determinants of U-I interaction the role of individual-level factors is also well explored. Several studies looking at academic engagement at the level of individual academics show that the most successful academics are also those who engage the most with industry (Gulbrandsen and Smeby, 2005; Bekkers and Bodas Freitas, 2008; Haeussler and Colyvas, 2011). In fact, academics' scientific productivity is generally found to be positively related to engagement with industry. Similarly, various studies find complementarities between the volume of funds that scientists raise from industry and government grants (Bozeman and Gaughan, 2007; Boardman and Ponomariov, 2009).

However, evidence is scant when it comes to the organisational context in which academic engagement occurs, especially with respect to the characteristics and research quality of the departments involved (Perkmann et al., 2013). Although academic engagement is clearly associated with individual academics' research standing, the same cannot be said when it comes to the organisation-level. The overall effect of organisation-level academic quality on participation in U-I collaborative activities has been found to be negative or mixed, as shown by D'Este and Patel (2007), Ponomariov (2008), Perkmann et al. (2011). D'Este and Patel (2007) show that scientists from departments that are poorly rated seem to engage in a wider range of interactions with industry, but this is only valid in the case of applied disciplines, whereas Ponomariov (2008) finds that the higher the average academic quality of an institution, the lower the propensity of individual scientists to interact with the private sector. Moreover, Perkmann et al. (2011) find support for a negative relationship between research quality and applied forms of academic engagement in the social sciences.

A possible explanation of such a negative relationship, contradicting previous findings of a positive relationship, is that a relatively low resource availability at lower quality universities may motivate top academics in these schools to seek industry collaboration in order to acquire research funds. In addition, the effect of a more prestigious research environment may be that academics perceive greater incentives to engage in blue sky research than to engage in interactions with industry. However, existing evidence has not been, so far, univocal with respect to this. In this paper we intend to shed more light on the existence of a negative relationship between research quality and academic engagement, hence, we put forward the following hypothesis:

Hp1: The lower is department academic quality, the higher is the volume of *industry funding raised for academic engagement*.

Notwithstanding the importance of research quality, this alone cannot fully explain the occurrence and the level of university-business interaction. Extant research has extensively focused on several contextual factors that may have an impact on the involvement of universities with firms, together with quality, notably geographical proximity, department/university size and previous experience. With respect to the latter, the attitude of academics towards industry as well as their collaborative behavior, are positively influenced by having collaborated in the past with companies (see e.g. Van Dierdonck et al., 1990; D'Este and Patel, 2007). Moreover, the likelihood of scientists' participation in academic engagement activities is also positively influenced by previous experience in patenting and other commercialisation activities (Bekkers and Bodas Freitas, 2008).

When previous engagement is measured with the volume of past funds raised by higher education institutions, it turns out that the ability to mobilise resources is generally positively linked to collaboration with industry (Perkmann et al., 2011; Bozeman and Gaughan, 2007). This may be due to the fact that universities' success in fund raising represents a signal for businesses, which hence leads to more opportunities and, arguably, more collaborating activities. This circular phenomenon recalls the so-called 'Matthew effect' (Merton, 1968), according to which greater recognition of merits often accrues to scientists of considerable reputation, whereas such recognition is withhold from scientists that 'have not yet made their mark' (Merton, 1968, pag. 58). In our case, this would imply that departments that have not yet engaged into collaboration with industry will be less known and hence, will have less opportunity to do so than departments who already have past experience.[1]

However, to the best of our knowledge, evidence on previous experience as a contextual factor with research quality is very limited. As previously mentioned, several studies find complementarities between the volume of government grants and the volume of funding raised from companies (Lee and Bozeman, 2005; Bozeman and Gaughan, 2007; Link et al., 2007;

[1]To put it in Merton's words: 'centres of demonstrated scientific excellence are allocated far larger resources for investigation than centres which have yet to make their mark' (Merton, 1968, pag. 62).

Boardman, 2009; Boardman and Ponomariov, 2009), but quality is not accounted for. In this paper, we intend to fill this gap and shed new light on the role of research quality when past experience is accounted for. We are interested in the existence of complementarities between past experience, specifically with government agencies, and department research quality. Therefore, on the basis of the existence of complementarities between past government grants and academic engagement, and the hypothesised negative relationship between the latter and research quality, we hypothesise the following:

Hp 2: The higher is past public funding, the higher is the impact of quality on the volume of industry funding raised for U-I collaboration.

In other words, we expect that public funds may enhance the role of quality, hence attracting higher levels of industry funding. The ability to raise public resources may be a signal for companies, in spite of quality levels, of universities and scientists' capacity to attract funds from government agencies, who may look positively at proposals from academic teams with past experience and that involve industry collaborators (Perkmann et al., 2013).

3.3 Data

The data for the empirical analysis consists of a set of university-industry research grants awarded to UK Universities by the Engineering and Physical Sciences Research Council (EPSRC) between 1992 and 2007, combined with university and department level information gathered from the UK Higher Education Funding Councils. In the analysis we focus on university-industry partnerships funded between 2001 and 2007 (measured with the amount of industry funding received by university departments in the whole period) and we study the role of past research quality and past experience in U-I collaboration (measured with financial contribution received from the EPSRC in the past) along with a number of other factors.

The EPSRC is one of the UK research councils responsible for administering public funding for research in the UK.[2] It is responsible for funding

[2]For further details see section 2.2.3.

research in the areas of engineering and physical sciences, including all the engineering fields, chemistry, mathematics and computer science, but it also welcomes research proposals that span the remits of other research councils, such as biology, social science or medical-related research. However, in this paper we restrict the analysis to collaborative grants within the main remits of the Council. In addition, although project partners may include companies, government agencies, public bodies, National Health Service (NHS) Trusts, non-profit organizations, and research and technology organizations, we only consider projects that involve UK university departments and companies. The EPSRC data used for the empirical analysis include information on the number of projects entered by each department, the size of the grants awarded by the EPSRC and the amount of cash or in-kind support (or a combination of both) provided by companies to the joint projects.

We gather information on departments and universities from the 2001 and 2008 Research Assessment Exercises (RAE), an evaluation exercise carried out in the UK approximately every 5 years, jointly by the Higher Education Funding Council for England (HEFCE), the Scottish Funding Council (SFC), the Higher Education Funding Council for Wales (HEFCW) and the Department for Employment and Learning, Northern Ireland (DEL). The primary purpose of the RAE is to provide ratings of research quality to be used by the UK higher education funding bodies in determining the main block research grants for the institutions they fund. Universities submit the results of their research activity for the assessment of all or some fraction of the research staff in the selected departments, within 68 subject research areas. Submission to the RAE is not mandatory but incentives for participation are high as public research funding depends on the assessment.

In addition to department ratings the RAE provides a number of other information, including department size (number of staff) and amount as well as sources of research funding received during the period under evaluation.[3] The RAE 2001 and 2008 pertain to the periods 1996-2000 and 2001-2007 respectively. Our main data source for the quality profiles

[3]Quality profiles are produced for the so-called Unit of Assessments, which can be linked to one or more university departments.

of university departments is the RAE 2001, since we are interested in departmental research quality as a determinant of future engagement with industry (from 2001 to 2008), whereas we collect other information from both the RAE 2001 and 2008, which we use to form a comprehensive set of control variables.

To build the dataset, we start by splitting the EPSRC data into two periods, each pertaining to one of the RAE: in the first one we include all partnerships funded between 1992 and 2000[4] and the second one includes all those granted from 2001 to 2007.[5] Secondly, after collapsing the data at university department level, we link each of them to the corresponding Unit of Assessment of the RAE (2001 and 2008) in order to merge all the relevant information that we need from each RAE. After repeating this for both periods, we merge the 2001-2007 dataset to the 1992-2000, so to end up with information on both periods for each university department. The final dataset includes 280 university departments that took part to at least one university-business partnership funded by the EPSRC in the first period (1992-2000) and, in most of the cases, in the second period[6] (2001-2007), and for which we collected data on both periods.

3.4 Method

In this paper we are interested in estimating the determinants of U-I collaboration. In order to reduce reverse causality issues between our dependent variables and our independent variables we frame the empirical empirical analysis in two different time periods: the first period concerns years 1992-2000 and the second one concerns years 2001-2008. We measure U-I collaboration with the volume of funding that university departments receive from companies in the second period (2001-2007). We consider both the total volume and the average amount of funding per project, calculated as the former divided by the number of grants obtained in the period 2001-2007. Therefore, we create two dependent variables, $IndFund_t$ and $IndFundGrant_t$, each of the two measuring the extent to which university

[4]These are 3,332 partnerships. Since only few (17%) have been funded before 1996, we include them in the first period and gather data from the RAE 2000 for them.

[5]These are 2,947 partnerships.

[6]Only 3 departments did not participate in the second period.

departments engage in U-I collaboration.[7]

We regress the dependent variables on a measure of department-level quality in period 1 ($t-1$) (independent variable), derived from the quality profiles published in the RAE 2001. We employ a dummy that takes value 1 if the department has been given a top rating in 2001. In the RAE 2001 each department submission is rated on a seven-point scale from 1 to 5*, with 5* being the highest score, indicating that research quality has achieved international excellence in more than a half of the departments' submitted activities, and the remaining activities have reached national excellence.[8] Hence, we create a dummy called $TopQualDep_{t-1}$, that takes value 1 if a department has been given one of the two highest ratings (5 or 5*).

It is worth underlying that the use of RAE rankings for the purpose of evaluating academic quality has both pros and cons. These rankings have been extensively used in the academic literature focused on UK research quality (see e.g. McGuinness, 2003; Abramovsky et al., 2007; D'Este and Patel, 2007; Ambos et al., 2008; D'Este and Iammarino, 2010; Perkmann et al., 2011). On the one hand, RAE results are considered reliable because they follow an expert review process conducted by assessment panels, whose members are nominated by a wide range of organisations, including research associations, professional bodies and those representing industrial, business and other users of research. On the other hand, it is arguable that they only provide partial and imperfect information about the overall quality of Higher Education Institutions. In the first place, panels' judgments, although made by experts who command a generally high level of respect, are subjective and hard to validate. Secondly, and perhaps more importantly, RAE scores are based on refereed publications, therefore departments that are more oriented towards the production of publishable research may be advantaged. On the contrary, departments that are more focused on teaching activity and/or engaged with private sector activities

[7]Since both variables are highly skewed and also include a few zeros, we transform them by taking the zero-skewness logarithm, i.e. each variable is added with a constant so that the skewness is zero and the logarithm can be taken. In Stata this is done with *lnskew0*. The newly created variables are called $LnIndFund_t$ and $LnIndFundGrant_t$. We also replicated our empirical exercise with the log-transformed variables and results do not change, with the exception of a slightly higher magnitude of some of the coefficients (see Appendix 3.10).

[8]The original scale is 1, 2, 3b, 3a, 4, 5 and 5*.

may be valued less. As a matter of fact, after RAE 2001 results have been published, some academics felt that their work was validated whereas others suggested that the RAE failed to account for high-quality strategic and applied research (Barker, 2007). Moreover, interdisciplinary areas also seem to have been discriminated against, although it is not easy to find evidence of this (Barker, 2007). Therefore, RAE based measures, like that one we will be using, should be always employed and interpreted with caution, given that they are an imperfect measure of academic standing.

We also include a number of control variables to properly identify the relationship between quality and academic engagement with industry. These are either measured at $t-1$ (period 1) or at time t (period 2), or are time-invariant. In the first place, we control for previous experience in U-I partnerships, using the amount of EPSRC funding awarded in previous years for U-I projects ($LnEsprcFund_{t-1}$). This captures previous experience that departments gain in carrying out research funded by the EPSRC and, hence, measures their ability to mobilise resources from government bodies. We are particularly interested in this variable because it helps understanding whether and to what extent research quality matters in the presence of previous experience.

In order to account for other streams of funding that each department received and that may be related to the volume of funds raised from industry, we control for the amount of total funding from the private sector (hence not only for projects funded by the EPSRC) that each department receives in period 2 ($LnInd_t$) as well as for the overall amount of non-industry funding received in period 1 ($LnNonInd_{t-1}$). We expect these to be positively related to our dependent variables since departments that raise funds from different sources are also likely to raise higher funds from companies. We also control for department size by including a continuous variable (in logarithm) that accounts for the number of research active staff in the department at the time of the RAE 2001 submissions ($LnDepSize_{t-1}$) and we expect larger departments to access higher amounts of industry funding.

We introduce control dummies for the scientific discipline and geographical location of the departments. As far as the former is concerned, we group the scientific disciplines into 4 categories and create 4 dummies to be included in the regressions: *BasicSci* for basic sciences (chemistry, physics, maths and statistics), *AppliedSci* for applied sciences (all engineering related sciences[9], computer science and environmental sciences), *SocSci* for arts and social sciences (arts, architecture, planning, management, and communication studies), and *MedSci* for medical sciences (medical and pharmaceutical studies, and biology). To avoid collinearity we exclude the prevalent category from the regression, that is applied sciences.

As for the geographical location of the university departments, the following region level dummies are included: East Midlands, East of England, London, North East, North West, Northern Ireland, Scotland, South East, South West, Wales, West Midlands and Yorkshire and the Humber. These captures region level factors that may affect the level of academic engagement with industry, including: local exogenous shocks, such as regulatory changes or the establishment of new companies, which enlarges the pool of firms to be potentially involved into U-I knowledge transfer, regional economic conditions, such as local innovative firms' absorptive capacity, quality of the labour market, and the implementation of new regional as well as national policies (Lawton Smith and Bagchi-Sen, 2012).

In the first place, we are interested in the relationship between department quality in period 1 and the level of academic engagement with industry in period 2. We posit that there may be a negative relationship, because top ranked departments ($TopQualDep = 1$) may need to attract industry funding to a lesser extent than low ranked department ($TopQualDep = 0$), due to their higher degree of resources availability (Perkmann et al., 2013). Moreover, academics in top universities may perceive greater incentives to engage in basic research than to engage in interactions with industry. In other words, for low-ranked departments U-I collaboration can be seen as a means to acquire research funds. Hence we estimate the following model:

$$Y_{it} = \alpha + \beta_1 TopQualDep_{it-1} + \gamma X_i + \epsilon_i \tag{3.1}$$

where Y_{it} is $IndFund_t$ or $IndFundGrant_t$, $TopQualDep_{it-1}$ is a dummy

[9] General, chemical, civil, electric, mechanic, and metallurgy and materials engineering.

that equals 1 for top departments and X_i indicates the set of control variables previously illustrated.

In the second place, we are interested in a moderating or enhancing effect of public funding on quality, which we test by adding an interaction term between $TopQualDep_{t-1}$ and $LnEsprcFund_{t-1}$. We argue that the effect that quality has on industry funding depends on the amount of previous public funding that each department receives from the EPSRC for U-I collaboration. The ability to raise public resources may be a signal for firms, of universities and scientists' capacity to attract funds from government agencies, beyond academic research quality. In addition, firms may expect that funding agencies look positively at proposals from academic teams with past experience and that involve industry collaborators. Therefore, we expect that past experience enhances the effect of quality, and we estimate the following model:

$$\begin{aligned} Y_{it} = \alpha + \beta_1 TopQualDep_{it-1} + \beta_2 LnEpsrcFunds_{it-1} + \\ \beta_3 TopQualDept_{it-1} * LnEpsrcFunds_{it-1} + \gamma X_i + \epsilon_i \end{aligned} \tag{3.2}$$

where $TopQualDept_{it-1} * LnEpsrcFunds_{it-1}$ is the interaction term in which we are interested and every other variable is as described in model (3.1).

We estimate both models with Ordinary Least Square regression with robust standard error to account for potential heteroskedasticity of the error terms (Angrist and Pischke, 2008). In addition, we test for the presence of multicollinearity using Variance Inflation Factors (VIFs) for all model specifications and the results are satisfactory. The VIFs are always fairly low (below 2) with the exception of the interaction and interacted terms.[10] In addition to the main estimations, we carry out a number of robustness checks. Firstly, we use a different measure of departments' past experience, namely the number of past collaborative grants funded by the EPSRC, instead of the volume of funding. We do so to verify whether our main results hold. Secondly, we replicate our analysis on the subsamples of departments that belong to basic and applied disciplines respectively, in

[10]An individual VIF greater than 10 or an average VIF greater than 6 typically indicate problems of collinearity. In our case, both individual and average VIFs are always below 2 with the exception of the interaction terms, which display high values because these are correlated with the interacted regressors.

order to check whether and to what extent the scientific domain matters in the relationship between research quality and academic engagement.

With respect to the correlation among regressors, we pay particular attention to the link between research quality and past EPSRC funding. The latter may be obviously related to quality because better departments may have higher interaction with public funding agencies, hence capturing a very similar effect to that of $TopQualDep$ on industry funding. On the other hand, it may also be that the quality rating of each department is positively influenced by having participated to EPSRC projects. However, we believe this not to be a major concern because of the ways public funding for research is allocated to UK universities.

Public research funding in UK higher education is administered under a 'dual support' system, according to which higher education funding councils provide the so called block grant funding to support the research infrastructure, and the Research Councils as well as other entities (e.g. charities, the European Union and government departments) provide grants for specific research projects and programmes. The block grant funding is allocated on the basis of research quality, as evaluated by the higher education funding councils themselves in the Research Assessment Exercise (now Research Evaluation Framework).[11] Ad-hoc grants for specific projects are instead allocated on the basis of different criteria. In particular, Research Councils employ independent expert peer review, consisting in the assessment for scientific quality by senior academics or peers from the UK and overseas.[12]

Therefore, in our case the amount of EPSRC funding that each department received between 1992 and 2000 is supposed to be independent from research quality in those years, as evaluated by the RAE 2001. Correlation will certainly exist between these variables. As a matter of fact, the statistical correlation between the two is 0.34. However, it is highly unlikely that this implies that research quality and the volume of EPSRC funds both measures academic standing and would be, hence, directly related to each other. Moreover, the RAE ratings have been published in 2001, whereas we only

[11] `https://www.hefce.ac.uk/`

[12] `http://www.rcuk.ac.uk/research/peerreview/`

include EPSRC funding received up to 2000 as a proxy for past experience.

3.5 Descriptive statistics

The list of variables along with their description is reported in table 3.1, and table 3.2 shows the descriptive statistics for all of them. Whenever a variable is log- or lnskew- transformed, we report both the level and logarithm. The total amount of funding from industrial partners within the EPSRC collaborations in period 2 ($IndFund_t$) is 1,5 million pounds, on average, per department, but it ranges from 0 (3 departments) to 15 million pounds; on average, each department gets 114 thousand pounds per project ($IndFundGrant_t$), peaking at 1,3 million pounds and each department received on average 10 grants during the years 2001-2008.

There are 280 university departments in our sample, 147 (52.5%) of which had a score of 5 or 5* in the RAE 2001 and 133 (47.5%) had a score of 2 to 4.[13,14] The number of people employed is between 1 and 167 (the mean is 28). The mean volume of funding received from the EPSRC in period 1 ($EpsrcFund_{t-1}$) is 2 million pounds, and the overall amount of industry funding, hence not only under the EPSRC projects, is on average 1,6 million pounds, peaking at 21 million for one university department only. As for funding received from public sources in period 2, the average is 1,1 million pounds.

As for the geographical distribution of university departments, 14.6% of them are in the Greater London Area, followed by 14% in Scotland and 12% in the South East. Instead, the regions with the smallest presence of departments involved in EPSRC U-I collaboration are the North East of England and Northern Ireland. The majority of departments are those of applied disciplines (60%), primarily engineering, and basic disciplines (32%), whereas only 7% belong to social sciences or medical sciences.

Table 3.3 shows the cross tabulation of the number of EPSRC U-I projects, industry funding (for EPSRC projects) and EPSRC funding (all at depart-

[13]In the full sample of 327 RAE 2001 Unit of Assessments that belong to the same disciplines as those in our sample, the percentage of departments that has been rated 5 or 5* is 41.

[14]None of the departments has been given the lowest rating (1).

ment level) per funding period along with the percentage change between periods. Interestingly, non top departments experience a quite large increase in the amount of industry funding received between funding periods, namely a 107% increase, and this is larger than for top quality departments (84%). This is supportive of the idea that lower ranked departments may attract industry funds for research to compensate for low quality.

3.6 Results

3.6.1 Main results

Tables 3.4 and 3.5 show the main findings of this work. In the first table we present the results of the OLS regression on the total volume of funds that university departments receive from companies under the umbrella of the EPSRC funded projects (dependent variable: $LnIndFund_t$). In the second table, the dependent variable is the mean volume of funding per project ($LnIndFundGrant_t$). In both tables, the first column includes only the full set of control variables. In the second and third column, the dummy for top schools ($TopQualDep_{t-1}$) and the amount of EPSRC past funds ($LnEsprcFund_{t-1}$) are introduced respectively, whereas both of them are there in the fourth column. Finally, the interaction term as in model (2) is added in the last column.

In table 3.4 we notice that quality is positively related to industry funding in column 2 and 4, whereas it has a negative coefficient in the last column. The coefficient is only significant at the 10% level in column 2 and at 5% level in column 5. Therefore, the relationship between quality and academic engagement remains partly ambiguous and the hypothesised negative effect of quality finds only partial confirmation in the data. As expected, the volume of funds that university departments receive from the EPSRC at $t-1$ (pre-2001), measuring past experience, is a strong predictor of the amount of involvement with industry at time t, during the period 2001-2007: the coefficient of $LnEsprcFund_{t-1}$ is positive and significant at 1% level in all the estimations. This means that the larger is the amount of financial involvement with the EPSRC (public funding) in period 1, the larger is the amount of industry funding attracted by university departments in period 2. Furthermore, when both past experience and research quality are considered (column 4), the latter loses significance. Therefore, quality does not seem to play a predominant role for academic engagement when past experience is accounted for.

Out of the other explanatory variables, the most relevant factors that predict U-I engagement include: department size, which is positively related to the dependent variable, although significant in the first three regressions only; the overall volume of industry funding $LnTotInd_t$, which is always positive and significant; as expected, the dummy for Social Sciences is negative and significant with respect to the baseline category of Applied Sciences; finally, the location dummy for West Midlands is positive and significant, implying that university departments located there display higher levels of involvement with industry with respect to the baseline region, which is London.[15]

In the last column, the interaction term $TopQualDep{*}LnEsprcFund$ is added to test whether the effect of quality on academic engagement with industry depends upon the amount of EPSRC funding received in the past by departments (model (3.2)). The coefficient of the interaction term is positive and significant (at 5% level), confirming our second hypothesis that public funds enhance the role of quality. In addition, the coefficient for $TopQualDep_{t-1}$ becomes negative and significant (at 5% level), supporting the existence of a negative relationship between quality and industry funding. The coefficient of $LnEsprcFund_{t-1}$ is now smaller but still significant at 1% level. The additional effect of EPSRC funding on industry funding for departments of high quality is 0.31, or an additional 3.1% increase in industry funding due to a 10% increase in EPSRC funding. Overall, low quality departments experience a 4.3% (0.430) increase whereas top quality departments experience a 4.3%+3.1%=7.4% increase in industry funding.

The results presented in table 3.5, in which the dependent variable is the mean per grant volume of industry funding, show very similar results to table 3.4, although slightly smaller in magnitude. Quality has a negative and significant coefficient in column 5, but positive in columns 2 and 4, al-

[15]This result is somehow unexpected given the distribution of university departments in our sample across the UK (see table 3.2) It may be due to the participation of some top departments from West Midlands universities that attract high levels of funding from private partners through U-I collaboration.

though not significant. Therefore, a negative relationship with the volume of mean industry funding is only partially confirmed. The interaction term is positive and significant, indicating that top quality departments experience a 0.7%+2.5%=3.2% increase in industry funding due to a 10% increase in past EPSRC funds, whereas non-top ones have a 0.7% increase. In addition, the volume of past EPSRC funds does not significantly predict the mean value of industry funds in the full model in column 5. As for the other controls, only the location dummy indicating departments located in the West Midlands display a positive and significant relationship with mean industry funding, as it was the case in the previous set of regressions.

The results obtained from the interaction terms can be better interpreted if pictured on a diagram. Figures 3.1 and 3.2 show the predictive margins of $TopQualDep_{t-1}$ for $LnIndFund_t$ (Figure 3.1) and $LnIndFundGrant_t$ (Figure 3.2), on the whole range of values of $LnEsprcFund_{t-1}$ (horizontal axis), as obtained from the regressions in column 5 in table 3.4 and 3.5 respectively. The interaction term that we introduce in our regressions allows the effect of an additional unit of past EPSRC funding to differ for top quality and non-top quality university departments.

In figure 3.1, for lower levels of past EPSRC funds, low quality departments receive higher industry funds than top quality ones, as shown by the fact that the blue line predicting values for non top-quality departments ($TopQualDep_{t-1} = 0$) lies above the red line for top departments ($TopQualDep_{t-1} = 1$). In other words, an additional unit of EPSRC funding in period 1 results in a higher amount of industry funding in period 2 for non-top university departments than for top departments. Therefore, EPSRC funds have an enhancing effect on quality, most likely because they act as a signal for departments to attract higher volumes of funding from industry. However, this is untrue for higher levels of EPSRC funds, where top quality departments receive higher levels of industry funds than low quality ones. In fact, after a threshold, an additional unit of past EPSRC funds has a larger impact on the volume of industry funding received by top quality university departments than non-top ones, shown by the fact that the predicting line for $TopQualDep_{t-1} = 0$ lies below that one for $TopQualDep_{t-1} = 1$. In figure 3.1, the threshold is at a volume of EPSRC funds of around 520 thousand pounds, at which both top and non top schools' predicted value of total industry funding in 2001-2008 is 300 thousand pounds.

Figure 3.2 shows a similar pattern since low quality departments get higher mean industry funding than top ones. However, this holds for almost the whole range of values of past EPSRC funding. In fact, the trend is the opposite only after a threshold of past EPSRC funds of around 900 thousand pounds, resulting in a predicted value of mean industry contribution per project of 60 thousand pounds for both top and non top departments.

3.6.2 Robustness check and further results

In order to check the robustness of our results and get additional insights from the data, we carry out three sets of regressions. In the first place, we replicate the analysis using a different proxy for departments' past experience with the funding agency. We choose the number of EPSRC U-I collaborative projects in period 1 (1992-2000) to measure the extent to which each department has been involved with the EPSRC in the past. With respect to the amount of money received by the EPSRC, the number of projects has the advantage to be less concentrated in a small number of departments. Moreover, it is less prone to measurement error due to misreported figures.

Secondly, in light of the fact that the relationship between research quality, as well as other factors, and academic engagement with industry may depend on the scientific field (Perkmann et al., 2011), we replicate our analysis on two subsamples of university departments that belong to basic and applied disciplines respectively. After excluding departments that fall under the social sciences and medical sciences, hence restricting the analysis on EPSRC related remits, we split basic and applied disciplines departments. By doing so, we wish to uncover different patterns in the relationship between department-level determinants and academic engagement with industry that depend upon the specific disciplines.

As far as the first set of regressions is concerned (see table 3.6), the results on both total industry funding per department and average funding per project per department are very similar to the previous findings of this work. The number of past projects funded by the EPSRC has very similar coefficients to those for the amount of funding received. Moreover, the results are confirmed as far as the interdependence between quality and past experience are concerned. Overall, this check supports the main finding of this paper, namely that the relationship between quality and academic engagement remains partly ambiguous, and that past experience enhances the role of quality.

Table 3.7 shows the results of the regressions carried on the subsample of university departments in basic sciences ($N = 92$), including maths, physics, chemistry and statistics, whereas table 3.8 presents the results for applied sciences departments ($N = 167$), including all engineering-related fields. Interestingly, there is a difference in the role played by academic quality across the two subsamples. For departments in basic disciplines (table 3.7), quality displays always a negative relationship with industry funding, though not always significant[16], whereas for departments in applied disciplines (table 3.8) the relationship remains ambiguous, being it positive and negative across different estimations.

The existence of a negative relationship between quality and industry funding in the basic sciences could be explained by the fact top departments that mainly carry out basic research are less likely to get involved into U-I interaction and attract industry funding. Similarly, firms may be reluctant to engage in research activities with departments mostly doing research that is less likely to be commercially viable. On the contrary, engineering-related disciplines are by definition closer to the business community and thus, it is reasonable to expect a positive link between academic quality and industry engagement.

3.7 Discussion and conclusion

This paper has investigated the relationship between university departments' characteristics and academic engagement with businesses in the form of university-industry (U-I) collaboration. In this paper, we focus on the role of the quality profile of academic departments for the level of engagement with industry. The latter is measured with the amount of

[16]It is also significant in a model with research quality and controls, without past experience.

industry funding that each university department receives when participating to U-I collaboration. We study the case of U-I partnerships that have been funded by the Engineering and Physical Sciences Research Council (EPSRC) in the UK and we hypothesise that a negative relationship between academic research quality and industry funding for academic engagement may exist, supported by the argument that industry funding compensates for low department quality. In addition, we investigate whether this relationship is influenced by departments' past experience in publicly funded U-I collaboration, measured with the amount of public funding received in the past.

The data consist of a set of university-industry research grants awarded in the UK by the EPSRC, combined with university and department level information gathered from the UK Higher Education Funding Councils. In the empirical analysis we focus on university-industry partnerships funded between 2001 and 2007 and we study the role of past research quality along with that of past experience and the interaction between them, plus a set of control variables.

Our findings only partly confirm the hypothesised negative relationship between quality and private funding for academic engagement because the coefficient has negative and significant sign in only some of the models that we estimate. On the one hand, lower quality departments may seek additional funding from business partners in order to compensate for low public resources - due to the lower quality of the research produced. On the other hand, academics in prestigious departments may be more incentivized to engage in basic research rather than engaging in collaboration with companies. However, further analysis is needed to confirm this.

Moreover, past experience with the funding agency, measured with the past volume of EPSRC grants for U-I collaboration, is positively linked to collaboration with industry. This may indicate that universities' ability to mobilise public resources represents a signal for businesses, which hence leads to more opportunities and, more generally, more collaborating activities. Therefore, similarly to previous studies (Bozeman and Gaughan, 2007; Boardman and Ponomariov, 2009), we find a complementarity between the past volume of public grants for U-I interaction and the volume of funding raised from companies.

To test our second hypothesis of an enhancing effect of past experience on research quality, we introduce an interaction term in the regression, between quality and past EPSRC funds, so to allow the effect of an additional unit of past EPSRC funding to differ for top quality and non-top quality university departments. The results confirm the hypothesis, since the coefficient is positive and significant. We further analyse the results by plotting the predicted values of industry funding for top and non-top quality departments and it turns out that only low levels of past EPSRC funds have a boosting effect on quality. In fact, for low levels of past EPSRC funds, low quality departments receive higher industry funds than top quality ones, whereas the opposite happens for high levels.

We also check the robustness of our results by using a different proxy for past experience with the funding agency. The results are quite satisfactory in that the coefficients are all very similar in magnitude and significance. Moreover, we carry out further analyses on university departments that are closely related to the EPSRC remits, namely basic and applied disciplines. It turns out that academic quality and industry funding display a negative relationship for departments in basic disciplines, which provides support for our first hypothesis. However, further research would be needed to shed more light on this.

This work has some limitations that is worth noticing. Although we frame our empirical analysis in two different time periods so to reduce reverse causality concerns, it is still questionable whether some factors are omitted in our econometric specification. If so, it would raise some endogeneity concerns. In addition, our study considers only one specific channel of U-I knowledge transfer activity, thus perhaps providing only a partial picture of the whole range of U-I activities in which universities are involved. Nonetheless, it is worth underlining that U-I research collaborations are extremely widespread in many advanced countries and are one of the most frequent policy instruments to support U-I knowledge transfer activities (OECD, 1998, 2002a).

Yet, this paper offers some contributions to the literature. In the first place, we bring new evidence on university-industry knowledge transfer activities and on their value by measuring them with the volume of industry funding and by exploring the role of department-level determinants. We attempt to show whether research quality displays a negative relationship with the volume of engagement with industry, but our findings are only partly conclusive. However, we show that research quality is interdependent with department past experience, since the latter may represent a signal for companies and boosts the effect of quality on the amount of resources raised from companies. More importantly, we show that past experience, measured with the volume of funds obtained for U-I collaboration by the funding agency, is a stronger and more significant predictor than quality. This finding suggests that public policy should substantially support university knowledge transfer, especially in light of the increasing costs of research for universities and companies, so to allow the best match of resources by both sides. Moreover, policy-makers could consider a division of labour among universities whereby some specialize in advanced research and others in business engagement.

3.8 Tables

Variable	Description	Period
$IndFund_t$	total contribution of industry partners to university departments for EPSRC funded projects	2001-2007
$LnIndFund_t$	as above, lnskew0 transformed	2001-2007
$IndFundGrant_t$	average contribution per EPSRC project from industry partners to university departments	2001-2007
$LnIndFundGrant_t$	as above, lnskew0 transformed	2001-2007
$NumPrj_t$	number of EPSRC projects per university department	2001-2007
$LnNumPrj_t$	as above, log transformed	2001-2007
$TopQualDep_{t-1}$	dummy for top departments (5 or 5*)	1992-2000
$EsprcFund_{t-1}$	total contribution from the EPSRC to university departments	1992-2000
$LnEsprcFund_{t-1}$	as above, log transformed	1992-2000
$TopqualXepsrc$	interaction term $TopQualDep_{t-1}$ x $LnEsprcFund_{t-1}$	1992-2000
$DeptSize_{t-1}$	number of staff per department	1992-2000
$LnDeptSize_{t-1}$	as above, log transformed	1992-2000
$TotInd_t$	total contribution from private sector to university departments	2001-2007
$LnTotInd_t$	as above, log transformed	2001-2007
$TotGovRc_{t-1}$	total public funding (government and research council) per university department	1992-2000
$LnTotGovRc_{t-1}$	as above, lnskew0 transformed	1992-2000
Region dummies	*eastmidu* (East Midlands), *eastengu* (East of England), *londonu* (London), *noreastu* (North East),	time invariant
	norwestu (North West), *noirelau* (Northern Ireland), *scotlanu* (Scotland), *southeau* (South East),	time invariant
	southweu (South West), *walesu* (Wales), *westmidu* (West Midlands), *yorkhumu* (Yorkshire & Humber)	time invariant
AppliedSci	all engineering subjects, computer science and environmental sciences	time invariant
BasicSci	chemistry, physics, maths and statistics	time invariant
SocSci	arts, architecture, planning, management, and communication studies	time invariant
MedSci	medical and pharmaceutical studies, and biology	time invariant

Table 3.1: List of variables

Variable	Obs	Mean	Std. Dev.	Min	Max
$IndFund_t$	280	1,517,703	2,688,188	0	1.51E+07
$LnIndFund_t$	280	13.0581	1.6585	10.01	16.5342
$IndFundGrant_t$	280	114,807.6	166,213.5	0	1,301,250
$LnIndFundGrant_t$	280	11.2108	1.0041	8.9998	14.085
$NumPrj_t$	280	10.525	10.9763	1	88
$LnNumPrj_t$	280	1.8495	1.075	0	4.4773
$TopQualDep_{t-1}$	280	0.525	0.5002	0	1
$EsprcFund_{t-1}$	280	2,043,875	2,851,427	19,959.77	2.36E+07
$LnEsprcFund_{t-1}$	280	13.7867	1.3219	9.9014	16.9765
$TopqualXepsrc$	280	7.4671	7.1755	0	16.9765
$DeptSize_{t-1}$	280	28.1571	22.6616	1	167
$LnDeptSize_{t-1}$	280	3.10357	0.6853	0	5.1180
$TotInd_t$	280	1,609,736	2,718,991	0	2.11E+07
$LnTotInd_t$	280	13.3307	1.4960	10.92	16.867
$TotGovRc_{t-1}$	280	1,135,152	2,871,275	0	4.48E+07
$LnTotGovRc_{t-1}$	280	13.3487	1.1337	11.3563	17.619
$eastmidu$	280	0.0821	0.2750	0	1
$eastengu$	280	0.0535	0.2255	0	1
$londonu$	280	0.1464	0.3541	0	1
$noreastu$	280	0.0392	0.1946	0	1
$norwestu$	280	0.0821	0.275	0	1
$noirelau$	280	0.025	0.1564	0	1
$scotlanu$	280	0.1392	0.3468	0	1
$southeau$	280	0.1214	0.3272	0	1
$southweu$	280	0.0785	0.2695	0	1
$walesu$	280	0.0535	0.2255	0	1
$westmidu$	280	0.0714	0.258	0	1
$yorkhumu$	280	0.1071	0.3098	0	1
$AppliedSci$	280	0.5964	0.4914	0	1
$BasicSci$	280	0.3285	0.4705	0	1
$SocSci$	280	0.0535	0.2255	0	1
$MedSci$	280	0.0214	0.1450	0	1

Table 3.2: Descriptive statistics

	1992-2000	%	2001-2007	%	Both periods	% change bw periods
Projects	3,332	100%	2,947	100%	6,279	-12%
top dept	2,278	68%	2,015	68%	4,293	-12%
non top dept	1,054	32%	932	32%	1,986	-12%
Industry funding (million £)	224	100%	425	100%	649	90%
top dept	167	75%	308	73%	475	84%
non top dept	56	25%	117	27%	173	107%
EPSRC funding (million £)	572	100%	951	100%	1,523	66%
top dept	418	73%	697	73%	1,115	67%
non top dept	154	27%	254	27%	408	65%

Table 3.3: Volume of U-I projects, Industry funding and EPSRC funding per funding period

VARIABLES	(1) $LnIndFund_t$	(2) $LnIndFund_t$	(3) $LnIndFund_t$	(4) $LnIndFund_t$	(5) $LnIndFund_t$
$TopQualDep_{t-1}$		0.360*		0.175	-4.070**
		(0.190)		(0.173)	(1.637)
$LnEsprcFund_{t-1}$			0.594***	0.583***	0.430***
			(0.0780)	(0.0792)	(0.106)
$Topqual * EpsrcF$					0.309**
					(0.119)
$LnDeptSize_{t-1}$	0.556***	0.462***	0.246*	0.206	0.204
	(0.168)	(0.176)	(0.138)	(0.144)	(0.140)
$LnTotInd_t$	0.430***	0.416***	0.187**	0.184**	0.159*
	(0.0744)	(0.0748)	(0.0776)	(0.0788)	(0.0808)
$LnTotGovRc_{t-1}$	0.149	0.150	0.0726	0.0745	0.0590
	(0.0959)	(0.0964)	(0.0802)	(0.0810)	(0.0789)
eastmidu	0.395	0.475	0.481	0.518	0.464
	(0.345)	(0.351)	(0.348)	(0.354)	(0.352)
eastengu	0.121	0.226	0.310	0.358	0.373
	(0.375)	(0.362)	(0.280)	(0.277)	(0.284)
noreastu	0.234	0.268	0.0623	0.0823	0.119
	(0.561)	(0.541)	(0.471)	(0.461)	(0.451)
norwestu	0.156	0.198	0.230	0.249	0.223
	(0.354)	(0.357)	(0.312)	(0.314)	(0.301)
noirelau	-0.0300	0.0668	0.386	0.425	0.420
	(0.530)	(0.509)	(0.393)	(0.392)	(0.402)
scotlanu	0.0927	0.150	0.0392	0.0680	0.0929
	(0.342)	(0.340)	(0.301)	(0.298)	(0.291)
southeau	0.0451	0.0793	0.147	0.162	0.122
	(0.285)	(0.287)	(0.259)	(0.261)	(0.255)
southweu	0.216	0.269	0.343	0.366	0.377
	(0.299)	(0.308)	(0.308)	(0.312)	(0.302)
walesu	0.203	0.265	0.0827	0.115	0.140
	(0.485)	(0.477)	(0.476)	(0.475)	(0.479)
westmidu	0.611*	0.626*	0.611*	0.618*	0.580*
	(0.360)	(0.367)	(0.327)	(0.331)	(0.330)
yorkhumu	0.369	0.365	0.233	0.233	0.234
	(0.348)	(0.350)	(0.296)	(0.297)	(0.296)
$BasicSci$	0.0470	0.006	0.0026	-0.0165	0.0126
	(0.214)	(0.209)	(0.183)	(0.182)	(0.181)
$SocSci$	-0.697**	-0.651**	-0.655*	-0.633*	-0.698**
	(0.302)	(0.297)	(0.345)	(0.351)	(0.353)
$MedSci$	-0.961	-0.817	-0.424	-0.363	-0.469
	(0.622)	(0.631)	(0.603)	(0.609)	(0.590)
Constant	3.461***	3.708***	0.475	0.651	3.242**
	(1.152)	(1.174)	(1.048)	(1.058)	(1.568)
Observations	280	280	280	280	280
R-squared	0.358	0.367	0.479	0.481	0.493

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3.4: OLS regression. Dependent variable: lnskew0 of $IndFund_t$

VARIABLES	(1) $LIndFundG_t$	(2) $LIndFundG_t$	(3) $LIndFundG_t$	(4) $LIndFundG_t$	(5) $LIndFundG_t$
$TopQualDep_{t-1}$		0.0663 (0.133)		0.00267 (0.132)	-3.500*** (1.256)
$LnEsprcFund_{t-1}$			0.201*** (0.0576)	0.201*** (0.0586)	0.0746 (0.0759)
$Topqual * EpsrcF$					0.255*** (0.0903)
$LnDeptSize_{t-1}$	0.192* (0.112)	0.175 (0.120)	0.0870 (0.104)	0.0864 (0.110)	0.0847 (0.106)
$LnTotInd_t$	0.130** (0.0511)	0.127** (0.0508)	0.0471 (0.0564)	0.0470 (0.0563)	0.0258 (0.0578)
$LnTotGovRc_{t-1}$	0.0866 (0.0665)	0.0867 (0.0668)	0.0608 (0.0637)	0.0608 (0.0639)	0.0481 (0.0625)
eastmidu	0.282 (0.243)	0.296 (0.247)	0.311 (0.252)	0.311 (0.256)	0.267 (0.251)
eastengu	0.261 (0.226)	0.280 (0.227)	0.325 (0.209)	0.326 (0.211)	0.339 (0.216)
noreastu	0.469 (0.313)	0.475 (0.309)	0.411 (0.302)	0.411 (0.302)	0.441 (0.297)
norwestu	0.248 (0.243)	0.255 (0.244)	0.273 (0.236)	0.273 (0.237)	0.251 (0.229)
noirelau	0.0758 (0.334)	0.0936 (0.333)	0.216 (0.310)	0.217 (0.310)	0.213 (0.319)
scotlanu	0.255 (0.238)	0.265 (0.240)	0.237 (0.229)	0.237 (0.231)	0.257 (0.227)
southeau	0.104 (0.214)	0.110 (0.216)	0.138 (0.213)	0.139 (0.214)	0.106 (0.209)
southweu	0.209 (0.223)	0.219 (0.224)	0.252 (0.232)	0.253 (0.232)	0.261 (0.222)
walesu	0.483 (0.399)	0.494 (0.400)	0.442 (0.398)	0.442 (0.402)	0.463 (0.404)
westmidu	0.584** (0.259)	0.587** (0.262)	0.584** (0.260)	0.584** (0.260)	0.552** (0.260)
yorkhumu	0.330 (0.241)	0.330 (0.242)	0.284 (0.227)	0.284 (0.228)	0.285 (0.226)
BasicSci	0.0018 (0.150)	-0.0057 (0.148)	-0.0131 (0.142)	-0.0134 (0.141)	0.0106 (0.140)
SocSci	-0.130 (0.248)	-0.122 (0.253)	-0.116 (0.281)	-0.116 (0.284)	-0.169 (0.279)
MedSci	-0.0144 (0.608)	0.0121 (0.614)	0.168 (0.619)	0.168 (0.624)	0.0812 (0.617)
Constant	7.493*** (0.830)	7.538*** (0.831)	6.482*** (0.849)	6.485*** (0.846)	8.624*** (1.153)
Observations	280	280	280	280	280
R-squared	0.126	0.127	0.164	0.164	0.187

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3.5: OLS regression. Dependent variable: lnskew0 of $IndFundGrant_t$

VARIABLES	(1) $LnIndFund_t$	(2) $LnIndFund_t$	(3) $LnIndFundG_t$	(4) $LnIndFundG_t$
$TopQualDep_{t-1}$	0.187	-0.526	0.0139	-0.490*
	(0.180)	(0.341)	(0.134)	(0.280
$LnNumPrj_t$	0.620***	0.470***	0.188**	0.0812
	(0.0983)	(0.114)	(0.0725)	(0.0856)
$Topqual * numPrj$		0.367**		0.259**
		(0.148)		(0.115)
$LnDeptSize_{t-1}$	0.273*	0.259*	0.117	0.108
	(0.145)	(0.140)	(0.112)	(0.108)
$LnTotInd_t$	0.190**	0.150*	0.0585	0.0304
	(0.0836)	(0.0870)	(0.0574)	(0.0594)
$LnTotGovRc_{t-1}$	0.108	0.0972	0.0743	0.0663
	(0.0859)	(0.0848)	(0.0654)	(0.0650)
eastmidu	0.533	0.492	0.314	0.285
	(0.340)	(0.345)	(0.249)	(0.250)
eastengu	0.292	0.311	0.300	0.314
	(0.291)	(0.293)	(0.214)	(0.216)
noreastu	0.187	0.229	0.451	0.480
	(0.473)	(0.463)	(0.308)	(0.307)
norwestu	0.215	0.216	0.261	0.261
	(0.335)	(0.335)	(0.244)	(0.244)
noirelau	0.367	0.382	0.185	0.195
	(0.423)	(0.426)	(0.320)	(0.324)
scotlanu	0.0812	0.116	0.244	0.269
	(0.310)	(0.301)	(0.233)	(0.229)
southeau	0.135	0.0945	0.127	0.0987
	(0.268)	(0.260)	(0.215)	(0.210)
southweu	0.327	0.349	0.237	0.252
	(0.322)	(0.310)	(0.232)	(0.224)
walesu	0.142	0.182	0.457	0.485
	(0.498)	(0.504)	(0.411)	(0.416)
westmidu	0.555	0.533	0.566**	0.550**
	(0.354)	(0.358)	(0.264)	(0.266)
yorkhumu	0.252	0.247	0.295	0.292
	(0.313)	(0.310)	(0.233)	(0.232)
$BasicSci$	-0.0201	0.0219	-0.0136	0.0161
	(0.190)	(0.188)	(0.144)	(0.142)
$SocSci$	-0.689**	-0.770**	-0.133	-0.191
	(0.344)	(0.351)	(0.278)	(0.280)
$MedSci$	-0.419	-0.498	0.133	0.0767
	(0.542)	(0.533)	(0.591)	(0.602)
Constant	6.751***	7.687***	8.459***	9.120***
	(1.246)	(1.318)	(0.897)	(0.947)
Observations	280	280	280	280
R-squared	0.451	0.462	0.148	0.163

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3.6: Robustness check. Dependent variables: lnskew0 of $IndFund_t$ and $IndFundGrant_t$

VARIABLES	(1) $IndFund_t$	(2) $IndFund_t$	(3) $IndFund_t$	(4) $IndFundG_t$	(5) $IndFundG_t$	(6) $IndFundG_t$
$TopQualDep_{t-1}$		-0.145	-6.602**		-0.368	-7.015***
		(0.382)	(3.059)		(0.306)	(2.165)
$LnEsprcFund_{t-1}$		0.669***	0.342		0.354***	0.0165
		(0.167)	(0.253)		(0.124)	(0.180)
$Topqual * EpsrcF$			0.474**			0.488***
			(0.227)			(0.162)
$LnDeptSize_{t-1}$	0.414*	0.326	0.350	0.0937	0.125	0.150
	(0.217)	(0.222)	(0.214)	(0.154)	(0.163)	(0.156)
$LnTotInd_t$	0.352**	0.100	0.0895	0.0827	-0.0518	-0.0631
	(0.134)	(0.138)	(0.141)	(0.0949)	(0.103)	(0.106)
$LnTotGovRc_{t-1}$	0.325*	0.0299	0.0179	0.179	0.0192	0.007
	(0.192)	(0.164)	(0.156)	(0.132)	(0.124)	(0.120)
eastmidu	0.729	0.442	0.192	0.438	0.181	-0.0756
	(0.508)	(0.431)	(0.393)	(0.273)	(0.300)	(0.291)
eastengu	0.334	0.701	0.541	0.785*	0.912**	0.747*
	(0.604)	(0.542)	(0.543)	(0.413)	(0.415)	(0.401)
noreastu	1.343*	0.906	0.670	1.114**	0.889	0.646
	(0.766)	(0.901)	(0.915)	(0.529)	(0.629)	(0.641)
norwestu	1.622**	1.293**	1.109**	1.002**	0.734	0.545
	(0.721)	(0.639)	(0.532)	(0.491)	(0.468)	(0.383)
noirelau	2.354***	2.106***	2.106***	1.734***	1.471***	1.471***
	(0.433)	(0.422)	(0.379)	(0.345)	(0.352)	(0.400)
scotlanu	1.641**	1.164**	1.162**	1.234**	0.917**	0.915**
	(0.664)	(0.554)	(0.530)	(0.474)	(0.459)	(0.437)
southeau	0.954*	0.703	0.591	0.686*	0.510	0.395
	(0.525)	(0.466)	(0.450)	(0.388)	(0.382)	(0.355)
southweu	1.263**	1.086*	0.964*	0.937**	0.776*	0.650*
	(0.577)	(0.567)	(0.529)	(0.415)	(0.447)	(0.369)
walesu	0.976	0.499	0.476	0.939	0.574	0.550
	(1.080)	(1.186)	(1.212)	(0.911)	(1.026)	(1.042)
westmidu	1.402*	1.100	0.849	1.075**	0.843	0.584
	(0.786)	(0.690)	(0.677)	(0.530)	(0.514)	(0.475)
yorkhumu	1.063	0.650	0.590	0.922*	0.661	0.600
	(0.775)	(0.629)	(0.637)	(0.546)	(0.474)	(0.482)
Constant	1.746	0.335	5.067*	6.603***	5.920***	10.79***
	(1.894)	(1.572)	(2.627)	(1.491)	(1.363)	(1.856)
Observations	92	92	92	92	92	92
R-squared	0.366	0.489	0.513	0.183	0.272	0.328

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3.7: Robustness check. Subsample of basic sciences departments

VARIABLES	(1) $LIndFund_t$	(2) $LIndFund_t$	(3) $LIndFund_t$	(4) $LIndFundG_t$	(5) $LIndFundG_t$	(6) $LIndFundG_t$
$TopQualDep_{t-1}$		0.403**	-2.131		0.294**	-0.129
		(0.199)	(1.848)		(0.138)	(1.382)
$LnEsprcFund_{t-1}$		0.532***	0.464***		0.120*	0.109
		(0.0900)	(0.111)		(0.0614)	(0.0775)
$Topqual * EpsrcF$			0.183			0.0305
			(0.134)			(0.0983)
$LnDeptSize_{t-1}$	0.738***	0.206	0.185	0.358***	0.190	0.187
	(0.208)	(0.208)	(0.210)	(0.130)	(0.140)	(0.141)
$LnTotInd_t$	0.496***	0.228**	0.206*	0.169***	0.0907	0.0869
	(0.0983)	(0.101)	(0.104)	(0.0644)	(0.0678)	(0.0683)
$LnTotGovRc_{t-1}$	0.0494	0.0736	0.0741	-0.0078	-0.0006	-0.0006
	(0.119)	(0.0996)	(0.101)	(0.0726)	(0.0714)	(0.0718)
eastmidu	0.646	0.926**	0.919*	0.615**	0.727**	0.726**
	(0.447)	(0.466)	(0.468)	(0.279)	(0.291)	(0.290)
eastengu	-0.0043	0.367	0.403	0.0626	0.216	0.222
	(0.471)	(0.339)	(0.347)	(0.276)	(0.251)	(0.253)
noreastu	-0.0755	-0.0987	-0.0499	0.377	0.398	0.406
	(0.677)	(0.535)	(0.525)	(0.355)	(0.328)	(0.327)
norwestu	-0.376	-0.273	-0.252	0.0639	0.0934	0.0969
	(0.383)	(0.348)	(0.357)	(0.261)	(0.261)	(0.265)
noirelau	-0.955	-0.167	-0.181	-0.412	-0.205	-0.207
	(0.640)	(0.415)	(0.417)	(0.345)	(0.312)	(0.313)
scotlanu	-0.633	-0.391	-0.364	-0.0357	0.0506	0.0552
	(0.408)	(0.375)	(0.373)	(0.269)	(0.267)	(0.269)
southeau	-0.301	-0.0897	-0.0986	-0.0564	0.0090	0.0076
	(0.349)	(0.326)	(0.323)	(0.253)	(0.253)	(0.254)
southweu	-0.182	0.115	0.132	0.0871	0.193	0.196
	(0.354)	(0.398)	(0.392)	(0.256)	(0.271)	(0.271)
walesu	-0.181	-0.110	-0.0604	0.250	0.280	0.288
	(0.519)	(0.489)	(0.494)	(0.392)	(0.386)	(0.390)
westmidu	0.271	0.399	0.421	0.495*	0.514*	0.517*
	(0.353)	(0.373)	(0.386)	(0.281)	(0.306)	(0.310)
yorkhumu	0.127	0.170	0.191	0.172	0.172	0.175
	(0.393)	(0.333)	(0.330)	(0.253)	(0.239)	(0.239)
Constant	3.646**	0.828	2.079	7.826***	7.441***	7.649***
	(1.559)	(1.551)	(1.921)	(0.990)	(1.094)	(1.308)
Observations	167	167	167	167	167	167
R-squared	0.453	0.566	0.570	0.237	0.279	0.279

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3.8: Robustness check. Subsample of applied sciences departments

3.9 Figures

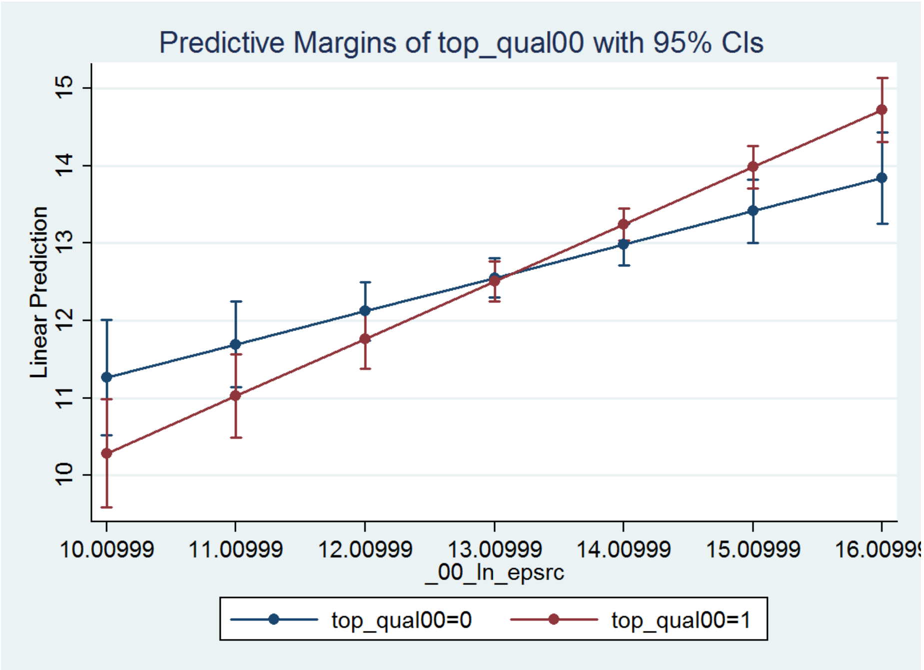

Figure 3.1: Interaction on $LnIndFund_t$

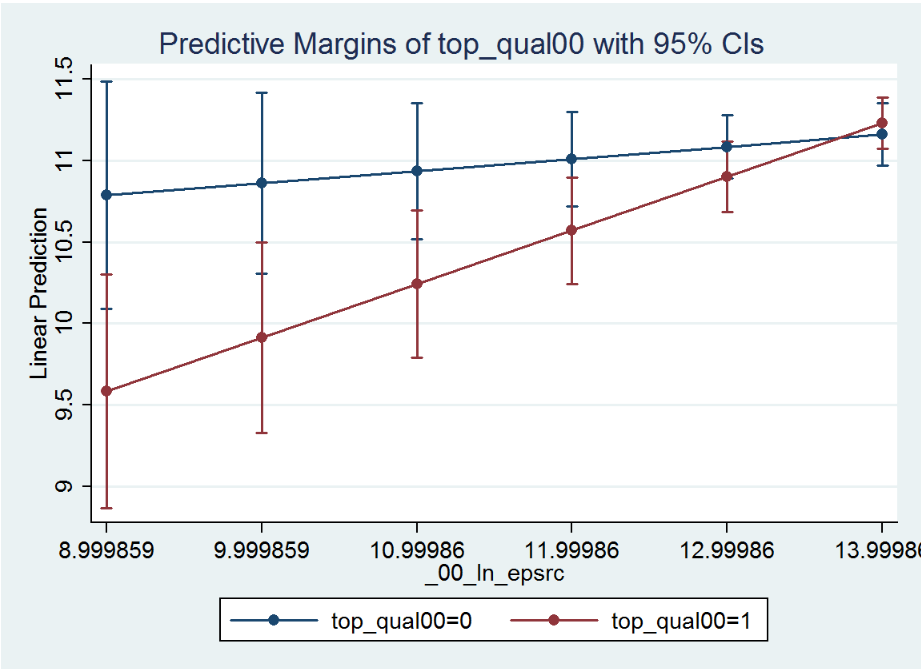

Figure 3.2: Interaction on $LnIndFundGrant_t$

3.10 Appendix

VARIABLES	(1) $LogIndFund_t$	(2) $LogIndFund_t$	(3) $LogIndFund_t$	(4) $LogIndFund_t$	(5) $LogIndFund_t$
$TopQualDep_{t-1}$		0.331		0.101	-4.937**
		(0.229)		(0.209)	(2.122)
$LnEsprcFund_{t-1}$			0.696***	0.690***	0.509***
			(0.0958)	(0.0968)	(0.128)
$Topqual * EpsrcF$					0.366**
					(0.152)
$LnDeptSize_{t-1}$	0.579***	0.493**	0.208	0.186	0.186
	(0.208)	(0.218)	(0.172)	(0.180)	(0.176)
$LnTotInd_t$	0.499***	0.487***	0.215**	0.214**	0.182*
	(0.0948)	(0.0956)	(0.0981)	(0.0991)	(0.101)
$LnTotGovRc_{t-1}$	0.157	0.157	0.0691	0.0698	0.0534
	(0.125)	(0.126)	(0.106)	(0.107)	(0.104)
eastmidu	0.403	0.479	0.500	0.523	0.455
	(0.444)	(0.452)	(0.447)	(0.452)	(0.448)
eastengu	0.207	0.307	0.432	0.460	0.472
	(0.420)	(0.410)	(0.320)	(0.321)	(0.325)
noreastu	0.253	0.289	0.0488	0.0617	0.100
	(0.668)	(0.648)	(0.569)	(0.561)	(0.545)
norwestu	0.0624	0.105	0.147	0.159	0.124
	(0.478)	(0.481)	(0.426)	(0.425)	(0.410)
noirelau	0.0624	0.155	0.549	0.572	0.562
	(0.603)	(0.585)	(0.452)	(0.452)	(0.462)
scotlanu	0.105	0.167	0.0281	0.0476	0.0651
	(0.437)	(0.435)	(0.387)	(0.383)	(0.377)
southeau	0.177	0.210	0.318	0.327	0.274
	(0.354)	(0.360)	(0.319)	(0.321)	(0.313)
southweu	0.371	0.424	0.519	0.534	0.542
	(0.368)	(0.377)	(0.374)	(0.377)	(0.365)
walesu	0.248	0.308	0.107	0.127	0.153
	(0.603)	(0.598)	(0.592)	(0.595)	(0.600)
westmidu	0.798*	0.815*	0.798**	0.803**	0.754*
	(0.426)	(0.433)	(0.388)	(0.391)	(0.389)
yorkhumu	0.390	0.390	0.230	0.231	0.228
	(0.443)	(0.444)	(0.382)	(0.383)	(0.381)
$BasicSci$	-0.0042	-0.0382	-0.0623	-0.0721	-0.0414
	(0.261)	(0.255)	(0.224)	(0.222)	(0.220)
$SocSci$	-0.771*	-0.727*	-0.723	-0.710	-0.788*
	(0.401)	(0.397)	(0.444)	(0.449)	(0.452)
$MedSci$	-1.571	-1.436	-0.950	-0.915	-1.042
	(1.114)	(1.132)	(1.111)	(1.122)	(1.105)
Constant	2.136	2.364	-1.366	-1.264	1.787
	(1.514)	(1.547)	(1.427)	(1.449)	(2.010)
Observations	277	277	277	277	277
R-squared	0.324	0.329	0.441	0.442	0.453

Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3.9: OLS regression. Dependent variable: natural log of $IndFund_t$

VARIABLES	(1) $LogIndFundG_t$	(2) $LogIndFundG_t$	(3) $LogIndFundG_t$	(4) $LogIndFundG_t$	(5) $LogIndFundG_t$
$TopQualDep_{t-1}$		0.0267 (0.168)		-0.0657 (0.167)	-4.543** (1.792)
$LnEsprcFund_{t-1}$			0.272*** (0.0753)	0.276*** (0.0769)	0.116 (0.0945)
$Topqual * EpsrcF$					0.326** (0.127)
$LnDeptSize_{t-1}$	0.210 (0.143)	0.203 (0.152)	0.0649 (0.132)	0.0798 (0.138)	0.0796 (0.134)
$LnTotInd_t$	0.172*** (0.0655)	0.171*** (0.0655)	0.0609 (0.0710)	0.0615 (0.0706)	0.0334 (0.0729)
$LnTotGovRc_{t-1}$	0.0984 (0.0875)	0.0984 (0.0877)	0.0639 (0.0827)	0.0635 (0.0826)	0.0489 (0.0806)
eastmidu	0.305 (0.338)	0.311 (0.342)	0.343 (0.348)	0.329 (0.352)	0.268 (0.345)
eastengu	0.362 (0.278)	0.370 (0.280)	0.449* (0.259)	0.431 (0.262)	0.442* (0.265)
noreastu	0.563 (0.386)	0.566 (0.383)	0.483 (0.370)	0.475 (0.373)	0.509 (0.364)
norwestu	0.162 (0.377)	0.165 (0.379)	0.195 (0.363)	0.187 (0.364)	0.156 (0.353)
noirelau	0.145 (0.406)	0.152 (0.406)	0.335 (0.377)	0.319 (0.375)	0.310 (0.384)
scotlanu	0.350 (0.306)	0.355 (0.307)	0.320 (0.293)	0.307 (0.295)	0.322 (0.291)
southeau	0.206 (0.279)	0.208 (0.281)	0.261 (0.275)	0.255 (0.275)	0.208 (0.268)
southweu	0.340 (0.281)	0.344 (0.281)	0.398 (0.292)	0.388 (0.291)	0.395 (0.278)
walesu	0.550 (0.497)	0.555 (0.499)	0.495 (0.495)	0.482 (0.502)	0.505 (0.504)
westmidu	0.744** (0.321)	0.746** (0.322)	0.745** (0.320)	0.741** (0.319)	0.697** (0.317)
yorkhumu	0.398 (0.314)	0.398 (0.315)	0.336 (0.295)	0.335 (0.295)	0.332 (0.293)
$BasicSci$	-0.0411 (0.191)	-0.0438 (0.188)	-0.0637 (0.180)	-0.0574 (0.178)	-0.0301 (0.175)
$SocSci$	-0.147 (0.322)	-0.144 (0.325)	-0.128 (0.363)	-0.137 (0.363)	-0.206 (0.358)
$MedSci$	-0.429 (0.979)	-0.418 (0.989)	-0.186 (0.994)	-0.209 (1.000)	-0.323 (0.991)
Constant	6.459*** (1.143)	6.477*** (1.154)	5.091*** (1.197)	5.024*** (1.210)	7.735*** (1.538)
Observations	277	277	277	277	277
R-squared	0.122	0.122	0.164	0.165	0.187

Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3.10: OLS regression. Dependent variable: natural log of $IndFundGrant_t$

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